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Portfolio Optimization for Multiple Group Credit Unions

A Thesis
Presented to
The Faculty of the School of Engineering and Applied Science
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In Partial Fulfillment
of the Requirements for the Degree of
Master of Science in Systems Engineering

Submitted by:

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Abstract

Recently passed legislation (H.R. 1151 Credit Union Membership Access Act) permits credit unions to add new select employee groups (SEGs) to their fields of membership. The field of membership defines the members served by a credit union. Given this new ability, along with guidance from the National Credit Union Administration (NCUA) to diversify, credit unions now have the opportunity to market their services to specific employee groups or industries which can reduce the overall risk to the credit unions' health or solvency. This thesis explores the use of Modern Portfolio Theory applied to a credit union's portfolio of assets (in this case SEGs or industries) using a mean-variance optimization technique (quadratic programming). Altman's Z-Score, a thoroughly tested and broadly accepted predictor of corporate failure, is used as an asset's "return" or "health" measure in the mean-variance algorithm and the variance of the Z-Score over a time interval is used as the "risk" measure. The algorithm can be constrained as necessary and used to develop an efficient frontier showing optimal portfolios for each viable level of health and risk. Credit union management can use the results of the optimization as a tool to assist in their decision making process regarding the addition of new SEGs. The thesis examines two credit union case studies in which the technique is applied.

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1. Introduction

1.1. Credit Union Definition

A credit union is a co-operative financial institution in which its members loan money to each other and earn dividends from the earnings on the loans. Members are united by *common bonds* and democratically control the credit union under federal or state regulation. Credit unions are exempt from federal income taxes. The *field of membership* (FOM) defines the members that the credit union serves. An element of a credit union's FOM may be an employer, a church, a school, or a community. Over the years, a credit union's field of membership may have been expanded due to mergers of other credit unions, sponsor companies going out of business, or requests from groups who are not associated with a credit union to be included in the field of membership. [Credit Union Land 1998]

Credit unions are unique among financial institutions in concept, structure, operating philosophy, and business practices. The financial services that credit unions offer their members, rather than earning returns for owners, are the primary reason for their existence. [Foote 1997]

Currently over 12,000 credit unions in the United States manage approximately $222 billion in assets for 74 million members (about one-third of the nation's adult population). [Overstreet & Rubin 1991]

The first credit union in the United States was organized in 1909. Although credit unions were originally organized within communities, greater success was achieved by

organizing to serve employee groups – particular government employees, teachers, railway workers, and telephone company employees. [Foote 1997]

1.2. Credit Union Legislation

In 1934, Congress passed the Federal Credit Union Act (FCUA), establishing a federal regulatory system. In 1970, the National Credit Union Administration (NCUA), an independent governmental agency, was created by Congress to charter, supervise, and regulate federal credit unions. Other legislative initiatives that have affected credit unions include the creation of the National Credit Union Share Insurance Fund (NCUSIF) within the NCUA to insure savings in all federal credit unions and many state-chartered credit unions; the Depository Institution Deregulation and Monetary Control Act of 1980; and the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA). [Foote 1997]

1.3. Fields of Membership

As stated, credit unions are organized around a defined field of membership, and each member shares a common bond of affiliation with other members. The field of membership is a key characteristic of a credit union, and is defined in its charter or bylaws as those who may belong to it and use its services. The common bond is a characteristic of the members themselves. Congress has recognized three types of federal credit union common bonds: occupational (these groups are known as *select employee groups* or **SEGs**) which make up 79.7% of federal credit unions, associational (14.4%), and community or residential (5.9%). [Overstreet & Rubin 1991] A federal credit union

may also consist of a combination of occupational, associational, and, in certain limited circumstances, community groups. [Foote 1997]

1.4. Business and Credit Union Failure

In the early 1980s, America was in one of the worst recessions the country witnessed since the Great Depression. Business failures soared. The recession began a shift in the American economy from "smokestack" industries to "service" industries. The future of many occupational-based credit unions tied to smokestack industries was in jeopardy. A study of the causes of credit union failures in the period 1981-1985 [NCUA Research Study No. 4 1987] found sponsor failure or employee cutbacks were a significant contributing factor to the failure of credit unions during this period. Employee reductions contributed in a major way to the failure of 26 percent of the credit unions analyzed in the study. Outright sponsor failure contributed in a critical way to 17 percent of the failures. These failures did not predominantly occur among financially weak credit unions. Over half of the failing credit unions were well managed and had been in operation for more than 20 years.

In 1981, 349 credit unions failed (See Table 1). In April 1982, the NCUA stepped in and tried to stem those failures. That is when the agency allowed federal credit unions to add multiple membership groups, or select employee groups (SEGs). [Johnson, E. 1998] The problems facing credit unions were based on the diversification of membership – not problems of asset diversification and maturity mismatch as with other financial institutions such as S&Ls [Burger & Dacin 1991]. Credit union fortunes were highly correlated with those of a single firm, or they were tied to the economic fortunes of a

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narrow community. If all the membership worked for the same firm, and the firm failed or was forced to make heavy layoffs of employees, the credit union lost membership, loan delinquencies rose and there was no way to meet the increased borrowing demands of members. The NCUA permitted federal credit unions to expand existing charters to include different membership groups, so long as each group had its own common bond.

Table 1: Failures of Depository Institutions

Year	Federal Credit Union Charters Cancelled	Failed Credit Unions	Failed Banks
1972	672	4	1
1973	523	50	6
1974	369	100	4
1975	334	153	13
1976	387	128	16
1977	315	142	6
1978	298	168	7
1979	336	169	10
1980	338	239	10
1981	554	349	10
1982	556	327	42
1983	736	253	48
1984	664	130	79
1985	575	94	120
1986	441	94	138
1987	460	88	184
1988	201	85	200
1989	307	114	206

Source: CBO Report: Reforming Deposit Insurance, September 1990

NCUA's policy did stem failures. In 1982, the upward trend of credit union failures reversed. The newly implemented policies allowed credit unions to diversify their memberships so they were no longer dependent on a single employer. These

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policies also brought credit union membership opportunities to employees of companies too small to start their own credit unions. [Johnson, E. 1998]

Not only had credit union failures subsided in 1983, but credit unions were actually thriving in the era of deregulation. The credit union growth rate was nearly 21% in 1983; federal credit unions added 7,000 membership groups representing 2.6 million people. [Johnson, E. 1998]

Since 1982, about 3,600 federal credit unions have expanded their charters to take in at least one SEG. Each credit union now has an average 40 SEGs with 72 members per SEG, according to a 1997 report by the Filene Research Institute. In other words, 10.5 million of the 44.2 million federal credit union members belong through SEGs, or about one of every four members. [Johnson, E. 1998]

The rapid changes in the interpretation of common bond and field of membership in the early 1980s were reflective of the rapidly changing environment for financial institutions. Failure to adapt would have meant failure to grow and perhaps even failure to survive. As credit unions have grown larger and expanded their fields of membership, they have increasingly come into more direct competition with other financial institutions that are also competing fiercely among themselves. The prime causes of this increased competition were the financial innovations beginning in the late-1960s and the massive deregulation of the financial services industry in the 1980s. [Burger & Dacin 1991] All financial institutions are attempting to expand their own "fields of membership". Growing competition, even among credit unions, is inevitable in the new financial environment.

1.5. Multiple Group Credit Unions and Diversification

On July 30, 1996, the U.S. Court of Appeals for the District of Columbia Circuit ruled that the Federal Credit Union Act permits only one common bond of occupation per federal credit union. This decision was issued as a result of a lawsuit filed in 1990 by the American Bankers Association and several banks in North Carolina challenging NCUA's authority to allow AT&T Family Federal Credit Union in Winston-Salem, North Carolina to add multiple groups to its field of membership. Acting on this decision, the U.S. District Court issued an order on October 25, 1996 barring the NCUA from approving new multiple groups. This decision immediately affected approximately 3600 federal credit unions. In addition, credit unions were prevented by this order from adding members from any group other than the credit union's "core" group of members. On December 24, 1996, the U.S. Court of Appeals granted a partial stay of the October 25 decision. Under the partial stay, credit unions could accept members from existing multiple groups and from the core group; however, credit unions could not add new groups. [House Committee on Banking and Financial Services 1997]

A recent legislative initiative, signed into law by President Bill Clinton on August 7, 1998 and known as the Credit Union Membership Access Act (H.R. 1151), gives credit unions the ability to expand their fields of membership and expressly permits multiple-group credit unions. This bill reversed a February 25, 1998 Supreme Court decision declaring multi-occupational common bonds illegal. [U.S. House of Representatives, H.R. 1151 Committee Report 1998] This court order had been the result of commercial banks efforts to restrict the competitive ability of credit unions through a narrow interpretation of common bond and field of membership.

Part of H.R. 1151's intent is to ensure the safety and soundness of credit unions by allowing diversification. Through diversification, stress on credit unions would be reduced during periods of corporate downsizing or closure. Also, the probability of failure of credit unions and of losses to the insurance fund would be lower.

If credit union fields of membership are closed they may be vulnerable to shocks, such as strikes, loss of jobs, the sponsor moving or going out of business, or the association or community facing economic hardships common to all in the group. Open fields of membership enable credit unions to gain diversity by occupation, employers, and geographic area. It also allows credit unions access to more potential members and creates the opportunity for economies of large-scale operation. With many members and a large asset base, credit unions can justify hiring more qualified management, acquiring technology, and offering more services. [Johnson, R. 1995]

Current NCUA Chairman Norman E. D'Amours told the House Banking Subcommittee on Financial Institutions that open fields of membership minimize credit union failures and payouts from the taxpayer-backed NCUSIF. [Johnson, E. 1998] Without this protection, credit unions would be placed at unnecessary risk because a downturn in a single industry or economic sector could affect the viability of credit unions limited to a single membership group.

D'Amours believes the 1982 NCUA ruling that allows federal credit unions to include SEGs is really an extension of common bond language in the 1934 act, because the 1982 ruling also was meant to promote safety and soundness. "It's a practical solution to promote stability in an era when businesses continue to come and go," says D'Amours. "In the highly mobile and technocratic society of our times, when businesses

are constantly changing, downsizing, or moving, it would be fundamentally unsafe and unsound to limit credit unions to shrinking or static memberships. Given the diversification of other segments of the American financial industry, it would also be countercultural."

D'Amours stated in an August 1996 NCUA Letter to Federal Credit Unions:

"The essential concept and objectives of the multiple group policy developed in 1982 have not changed and remain an important tenet of current field of membership policy. The multiple group policies provide important benefits to NCUA, credit unions and credit union members. Credit union failures have been prevented; credit unions have been able to diversify and strengthen their financial soundness while reaching previously unserved groups; and credit unions have continued their commitment to serve low-income individuals and communities. We believe that the multiple group policy [is] legally sound and operationally critical."

Administrators of credit unions based heavily on a single SEG state that the closure of their parent company would have devastating effects on the continued financial viability of their credit unions. [Szaroleta and Mavico 1998] They would be forced to quickly re-charter and seek out new SEGs to ensure future growth and stability.

Credit unions cannot add membership groups at random. NCUA's Chartering and Field of Membership Manual details how credit unions can add groups through charter amendments approved by the agency's regional directors or the NCUA board. For example, a group to be added to a credit union's FOM must have its own common bond. Groups of people with occupational common bonds must be located within 25 miles of a credit union service facility. The group also has to request credit union service. NCUA considers the economic feasibility of adding a membership group, and it looks at potential overlap conflicts with other area credit unions.

The NCUA Chartering and Field of Membership Manual states that adding select groups to existing multiple group credit unions requires a written determination that a group cannot form its own credit union.

Multiple group credit unions may serve a combination of distinct, definable occupational and associational common bonds. Five statutory criteria must be met before a select group can be added to a credit union, and the group must be within the service area of one of the credit union's service facilities. An automated teller machine (ATM) does not meet the definition of a service facility.

Control of the common bond is one form of regulation not rigorously considered by current literature; however, Taylor (1971) describes some problems with common bond requirements and Burger and Dacin (1991) thoroughly review common bond history. Hall (1989) states that the liberalization of common bond requirements has been the source of considerable controversy within the financial services industry, but little research has been done to determine potential effects. If the liberalization trend continues, how will credit unions be affected? Credit union needs for diversification and growth must be considered within this context.

1.6. The Effects of FOM Diversification

In 1983, NCUA sent a questionnaire to credit unions that had expanded their field of membership to ask why they expanded, effects of expansion, future expansion plans, and comments on NCUA policy [NCUA, Field of Membership Study 1984]. The responding credit unions emphasized the economic benefits associated with expanding field of membership. About two-thirds of the respondents indicated they expanded their field of

membership: 1) to provide growth and expansion, 2) to provide service to new groups, 3) to offset reductions of existing membership, and 4) to add stability to the field of membership by diversification of groups.

A 1987 NCUA study of the effects of field of membership expansion [Solt] found credit unions that expanded their field of membership in 1983 and 1984: 1) maintained or improved their financial performance, 2) did not experience harmful effects on their capital position, 3) decreased their ratio of delinquent loans to total loans slightly more than non-expanding credit unions, 4) had earnings similar to non-expanding credit unions, and 5) were more likely than non-expanding credit unions to offer new services to members.

1.7. Portfolio Approach

The capability to diversify allows credit unions to employ a macro or portfolio approach to the evaluation of its member groups. Analysis can be conducted to determine the overall health and risk characteristics of the member group portfolio based on a health/risk profile and correlations of the individual member groups. Optimization routines can then be applied to identify new member groups to which the credit union could market its services, reduce its overall portfolio risk, and simultaneously continue to maintain a particular desired level of health. How a credit union can go about conducting this portfolio analysis and optimization is the question to be explored by this thesis.

2. Background

2.1. General

Credit unions have been under-researched despite their rapidly developing importance in the U.S. financial system. Limited empirical and theoretical work has been conducted into credit unions relative to the enormous body of research into other financial institutions. This is partly due to the fact that credit unions do not fit into the profit-maximizing, shareholder-owned model of banks.

2.2. Credit Union Objectives

The body of literature focused on credit union objectives is largely devoted to the borrower/saver conflict, and results in a number of relevant models. However, according to Overstreet and Rubin (1991), credit union theory is still deficient with much of the supporting empirical research either outdated or analytically limited. A failure to properly capture temporal effects in the theory and dated empirical results are among the primary weaknesses of the literature. Additionally, historical aspects of credit union evolution have not been rigorously treated.

It is difficult to identify a single credit union goal and therefore specification of a credit union objective function is controversial. The "cooperative principles" of credit unions include providing low-cost credit and high yielding deposits, building financial stability, and serving an open membership with financial services. These foundations are discussed in Ownership Makes a Difference (1987); Melvin, Davis, and Fischer (1977);

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Moody and Fite (1971); and Report of the Committee on Credit Union Uniqueness (1988).

The following are some of the suggested objective functions for credit unions:

- Maximize preference to borrowers and savers. [Smith, D.J. 1980]

- Maximize total distribution to borrowers and savers while maintaining neutrality between the two groups. [Smith, Cargill, and Meyer 1981]

- Minimize costs (of the internal spread between the credit union's loan and share rate). [Taylor 1971]

- Maximize the utility of reserves. [Chateau 1980]

- Maximize profits [Hempel and Yawitz 1977]

- Maximize size [Smith, P.F. 1971]

2.3. Credit Risk Management

There are two types of risk in credit management. The first is *systematic* or market risk that is the degree to which a portfolio moves with the general market. This type of risk cannot be diversified away. The other type of risk is *unsystematic* which results from events affecting an individual or company (e.g. a change in management, a new patent, etc.). Diversification can reduce this type of risk. [Morsman 1993]

Managing diversification requires an unpleasant trade-off with customer or loan volume. [Morsman 1993] Concentrations available for analysis include individual borrowers, industries, geographies, and credit products.

Until recently, most risk management business processes for credit institutions have focused on traditional, transaction-level analysis. Banks typically analyze the borrower's

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financial condition, determine a risk rating, obtain approval for the loan, set the terms and conditions, and process the transaction. [Aguais 1995]

To evolve from the transaction view to the portfolio view, Aguais believes that credit institutions can implement a combination of applications that may include, for example, default-based risk rating, detailed financial spreading and monitoring, risk-adjusted capital allocation, risk-adjusted loan pricing, and portfolio optimization.

2.4. Modern Portfolio Theory and Diversification Strategies

A long-time staple in the securities industry, modern portfolio theory (MPT) is slowly making its way into the credit and banking industries. The Office of the Comptroller of the Currency (OCC) has asked credit institutions to view risk management using a portfolio approach. [Hyndman 1997] MPT and new tools for analyzing risk offer opportunities for credit institutions to improve their well being without incurring additional risks or costs.

Portfolio management is not a new concept in finance. Mutual fund managers and investment advisors have used it for decades, while credit institutions have been slower to embrace these techniques.

Quantitative portfolio theory rose from academic research begun in the 1950s that focused on rates of return in the stock market. Using quantitative models, academics such as Harry Markowitz, James Tobin, and William Sharpe tracked stock prices and their covariances over time. The research of these and others culminated in what we now call MPT.

Using volatility of return as a surrogate for risk, Markowitz and others launched an assault on conventional investment thinking. They constructed a model focused on expected value (the "return" component) and standard deviation or statistical variance (the "risk" component). Risk and return were then plotted along two axes and it was shown graphically how one could construct an efficient frontier of optimal portfolios that minimized risk for each level of desired return. The methodology employed is often referred to as mean-variance optimization.

Figure 1 shows just how composing portfolios with several assets (in this case common stocks) can reduce risk. The first column indicates the number of stocks in the portfolio; the second column shows the level of variability (variance) above the basic market variability for a stock portfolio of that size. Basic market variability – the effect of changes in general economic activity on the returns of all stocks – cannot be eliminated. Judicious portfolio construction can, however, reduce almost completely the remaining variability – the non-market-related risk. The most dramatic reduction in non-market-related risk is achieved with about 14 stocks. The same diversification effect can be seen with assets other than stocks. For this thesis, the assets will consist of the industries or individual companies in the field of membership of credit unions. Diversification reduces risk. MPT's concept of risk as variability of portfolio returns rather than that of returns of individual assets does, in fact, work.

Figure 1: Risks of Portfolios with Different Numbers of Securities Whose Returns Are Uncorrellated

Number of Securities	Standard Deviation of Return in excess of the Standard Deviation of the Market
1	10.00%
2	7.07
3	5.77
4	5.00
5	4.47
10	3.16
20	2.24
50	1.41
100	1.00
1,000	.32
5,000	.14
10,000	.10
100,000	.03

Source: Sharpe (1999)

To apply Markowitz' theory, first the investor must choose among all possible investments on the basis of their risk (portfolio variance) and return (portfolio return). These two characteristics can be plotted on a graph such as in Figure 2.

Figure 2: The Efficient Frontier

Expected Return

Risk
(Variance)

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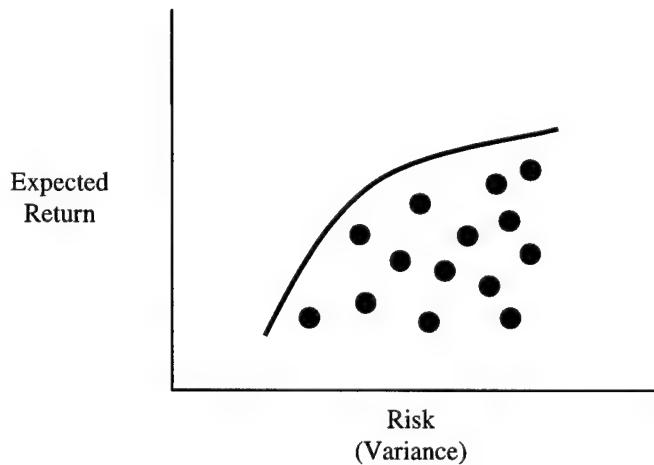
Each dot represents a possible investment. Some of the dots represent a single asset, whereas other dots represent various combinations of assets. The portfolios are made up of all possible combinations of the individual investments' alternatives. Thus, all possible choices are shown on the graph.

Next we must determine how an individual chooses among all possible portfolios. If the investor is rational, he or she will choose investments that provide the highest return for a given level of risk or those that offer the least risk for a given return. These best-return portfolios are called *efficient*. The curved line in Figure 2 is called the *efficient frontier*.

All possible efficient portfolios are identified but we have not given the investor directions as to how to choose his or her particular portfolio. This choice depends on the investor's appetite for risk. A risk-averse investor may prefer a portfolio with low risk (variance), whereas a risk taker may prefer a portfolio with greater variance and commensurately higher returns.

Plotting his or her trade-offs between risk and return can graphically represent an investor's risk preference. The lines connecting these points are called *utility curves*. Figure 3 shows the efficient frontier and a set of utility curves (dashed lines) that may reflect a risk-averse investor's preference for risk and return.

Figure 3: The Efficient Frontier and Investor Utility Curves
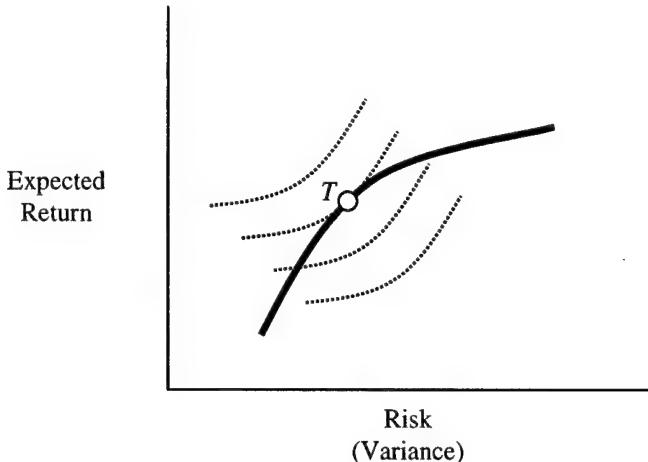
As risk increases along each utility curve, the return required to induce this risk-averse investor to take the risk must also increase. Each curve shown represents a single combination of risk and return equally satisfactory for this particular investor. The higher the utility curve, the greater the investor's satisfaction. Obviously, the investor's goal would be to find an investment, or portfolio, that would bring the greatest satisfaction. This would be an investment that lies on the curve that is highest and farthest to the left (most "northwest"). In this case the best that the investor can achieve is an investment that lies at the point at which the dashed utility curve touches (is tangent to) the efficient frontier. This is represented by the point *T* in the figure. A number of investments lie on lower utility curves, but these would not give this investor as much utility (satisfaction) as an investment on the frontier.

Other investors with different attitudes toward risk would have different utility functions (sets of utility curves). These curves define which investments, of all those on the efficient frontier, would be attractive to any given investor.

2.4.1. Assumptions Behind Modern Portfolio Theory

When modern portfolio theory was first described, investors and investment managers greeted it with a less than enthusiastic response. There were several reasons for this. First, the MPT model is normative, not descriptive; it describes what should be, not necessarily what is. On the basis of certain logical economic objectives, the theory describes idyllic investor behavior. MPT did not attempt to describe what had been observed in the marketplace.

Ordinarily, the normative quality of a model would not daunt an investment practitioner. It was a second problem that caused more dismay. MPT is based on certain assumptions that some practitioners considered to be "ivory tower" distortions of reality. Although all theories abstract fundamental relationships from complex environments, what made practitioners suspect these assumptions was that overzealous proponents of theory tended to emphasize the model's most basic assumption, that of the market's efficiency. The efficient market dogma is particularly bothersome to practitioners, as it seems to say that research and active management have not added value to portfolios and will not do so in the future. Furthermore, index funds based on the concept of market efficiency, portfolios constructed to imitate the market, added an observable threat to the implicit message that security analysis was worthless. Under the circumstances, it could hardly be expected that investment professionals would greet this theory with open arms.

For academics, the concept of risk as relative volatility had intuitive appeal. Just as they looked to the free market as the arbitrator of true security value, so did they look to market action as the arbitrator of relative riskiness. [Harrington 1987] The model seemed sensible.

Academics are much more accustomed than practitioners to working with simplifying assumptions. They tend to be more concerned with the acceptability of a theory's implications, pending its empirical verification, than with its perfect veracity. The academic world is also accustomed to working with "foundation" models – models that oversimplify reality. Academics know that, in time, these models are usually revised and elaborated to incorporate more realistic assumptions. A foundation model serves as a point of departure. If later testing proves that the assumptions are too strict and abstract, the assumptions can be modified.

The MPT model is simple, is controversial, and holds promise. The advantage of a simpler model is that it is easier to understand, test, and use. Although we do not want a model that is so simplistic that it ignores important factors, a model's purpose is to abstract from the noisy complexity of reality [Harrington 1987]. To be useful, a model must either describe what is occurring or forecast the future. A good model will both describe and forecast as simply as possible. A complex model would be of marginal value if a simple model could explain most of the variability of past returns and could predict the future with reasonable accuracy.

Harrington provides a good summary of the assumptions that underlie the efficient-market hypothesis and thus MPT:

1. The investor's objective is to maximize the utility of terminal wealth.

MPT is just a model that describes how investors make choices. Thus we must begin a theory of investor choice with a description of the objective the investor has in mind. We assume that the investor's objective is to maximize the utility of wealth at the end of a given holding period. For MPT, the investor is maximizing the *utility* of wealth, not

maximizing wealth (or return) itself. To make this description useful, we must describe the criteria that investors use in choosing among investments. We assume that investors take risk and return alone into consideration when maximizing their utility of terminal wealth.

2. Investors make choices on the basis of risk and return. Return is measured by the mean returns expected from a portfolio of assets; risk is measured by the variance of these portfolio returns.

Although there is little disagreement over using the mean expected rate of return as the measure of return, using variance as the measure of total risk has provoked controversy. The obvious advantage of using variance as the measure of risk is that it allows us to describe any distribution of returns by using only two numbers, the mean and variance. The key problem in using variance is that it is an accurate description only for normal distributions. Not all distributions are normal, as many researchers have shown. Distributions may have identical means and variances, yet they may still be quite different. In fact, it is intuitively obvious that distributions of returns in the capital markets are not normal. Although an investor can loose 100 percent of most investments, the upside potential is theoretically unlimited. Because of the normality assumption, any skewing of the returns' distribution is ignored by the model's use of variance as the sole measure of risk.

One solution to this problem is to substitute for variance some other measure of risk. Semivariance is one alternative and it measures only the downside risk (or upside potential) from the investor's chosen target, instead of measuring both up and downside

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from the mean. Variance and semivariance will yield the same results only when the distribution is normal and the investor's return target is the mean.

We can easily imagine an example in which the MPT mean-variance frontier would differ from that calculated on the basis of mean and semivariance. Any group of assets with skewed returns distributions would produce these contrasting results. Portfolios that would appear efficient on the basis of mean-variance criteria would appear inefficient on the basis of mean-semivariance criteria, and vice versa. Because the investor's decision would depend on the risk measure chosen, it is important to use an appropriate measure of risk.

In using MPT, we assume that portfolio variance is an appropriate measure of risk because it allows us to use two factors, mean and variance, to describe each asset's relative attractiveness.

When the first two assumptions are joined – that the investor's goal is to maximize the utility of terminal wealth and that the investor's decisions are based on expected risk and rates of return – we conclude that investors choose only those portfolios with the highest rate of return for their preferred level of risk (variance), or those with the lowest risk for their preferred rate of return.

Regardless, with only these two assumptions, every investor could have his or her own estimates of mean and variance for each asset, and thus each would have a unique efficient frontier.

3. Investors have homogeneous expectations of risk and return.

This means that all investors' estimates of risk and return are the same. To have a single efficient frontier of MPT, we must have consensus estimates of the mean and

variance and thus of the relative value of each investment. Without a consensus, each investor or group of investors could have very different forecasts for variance and for mean return. Consequently, the efficient portfolio for one investor could be quite different from that for another.

4. Investors have identical time horizons.

This assumption suggests that investors form portfolios to achieve wealth at a single, common terminal date. That single, common horizon allows us to construct a single-period model. The model implies that investors buy all the assets in their portfolios at one point in time and sell them at some undefined but common point in the future.

Although necessary, this assumption is obviously unrealistic. The world of investors is composed of short-term speculators, buy-and-holders, and everyone in between. Furthermore, the chosen horizon may depend upon the characteristics of the asset and could even change for any group of investors over time. This single-period assumption implies that investors operate on a single horizon. Yet investors act as if they make a series of reinvestments rather than a single-period buy-and-hold decision. Thus, a continuous model may be more appropriate.

Continuous-time models have been developed, but they are more complex than single-period models. However, these models continue to see risk and return as the only important characteristic of an asset. Other characteristics are believed to be completely summed up in the measures of risk and return.

5. Information is freely and simultaneously available to investors.

If groups of investors were privy to special, not widely available, information on which they could make superior decisions, markets would not be efficient and MPT

would be affected. Without a set of common forecasts, a single efficient frontier could not exist.

Although these assumptions are clearly not realistic, we must remember our criterion for a good model: does it explain or forecast or both? If it does either or both, we can use it to make better decisions.

2.4.2. MPT for Credit Institutions

Although intuitively intriguing, MPT has been difficult to apply to credit institutions. The assets of credit unions for instance consist of loans to members and deposits of the members. These assets are not as uniform or measurable as stocks. Furthermore, unlike securities, loans prepay, are restructured and have fluctuating payment streams caused by variable interest rates. [Hyndman 1997] Another way to look at the assets of a multiple group credit union is to examine the field of membership. The select employee groups for the credit union each come from a specific company or organization. Therefore, it could be asserted that the credit union has a group of companies or organizations as its assets.

In the past decade, analysts and academics have made some progress in applying portfolio theory to credit risk management. The San Francisco based consulting firm, KMV, was one of the first to attempt to quantify loan risk by using portfolio theory. A bank and vendor group led by J.P. Morgan developed a software package called CreditMetrics which is a mechanism for calculating value-at-risk. The group expects the CreditMetrics methodology to become the industry standard for portfolio management techniques in banking. [Hyndman 1997]

One of the important conclusions of modern financial theory is that investors should reduce risk by holding a diversified portfolio of assets. An implication of this conclusion is that investors should evaluate a potential new investment not in isolation but in terms of its impact on their portfolios. Concentrations of portfolios can be calculated by industry or geographic region. For example, the industry concentration of the portfolio can be calculated using the total value of loans in each industry as the appropriate weights. [Ford 1998]

In it purest form, active portfolio management entails empowerment of the portfolio management function to manage the loan portfolio to maximize value within defined risk parameters. In addition to shifting more power to portfolio managers, this action raises fundamental questions of business purpose. In effect portfolio management leaves its customer relationship roots behind and evolves into proprietary investing activity on behalf of the credit institution. [Asarnow 1996] This departure clashes with the fact that many banks define their business as being "customer-focused".

Diversification of a loan portfolio can be achieved by creating a portfolio of loans with uncorrelated probabilities of default. Ignoring the correlations between borrowers can lead to an underestimation of portfolio risk by 50%. [Chirinko & Guill 1991]

2.4.3. MPT for Loan Pricing

Before we examine the use of Modern Portfolio Theory as a tool for the management of credit union portfolios, it is appropriate to look at its use in other areas of credit risk management. One of these areas is in the pricing of loans. Loan pricing mechanisms most commonly used by banks are: (1) risk-based (relative to the risk of a

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particular loan), (2) customer relationship pricing (customer traits such as the variability of deposits and the length of the relationship influence loan pricing), and (3) modern portfolio theory in which prices are marked up/down from a standard based on the risk contribution of the loan to the portfolio. [Chmura 1995]

Risk-based pricing suggests that the expected return of a loan if paid in full should increase as the risk associated with the loan increases. A higher return is necessary to entice banks to hold riskier loans whose probability of default is relatively high. When the risk of a loan is too high or when the demand for loans exceeds supply, banks ration some potential customers out of the market by raising the contract interest rate. Thus, price serves as a rationing mechanism. [Chmura 1995]

Portfolio theory builds on risk-based pricing by indicating that banks should not be concerned only with the risk of a single loan but with each loan's contribution to the risk of the total loan portfolio. If a bank holds many different types of loans (a diversified portfolio), it can achieve a lower variability of actual loan losses for the same rate of return. Lower variability occurs because a lower return correlation among loans translates into a lower variability of return for the entire portfolio.

For example, loans with probabilities of default negatively correlated with the expected return on the bank's loan portfolio should be assigned lower interest rates than loans that default when the bank's loan portfolio is incurring a relatively high rate of losses.

Flannery states that borrowers should be sorted into categories that capture the bulk of shared reactions to external shocks. He suggests as a methodology the evaluation of

historic experience using statistical techniques to infer past relations among borrower or loan types.

Portfolio return, as used in a case study by Christine Chmura (1995), is simply interest income minus charge-offs net of recoveries divided by total loans. Risk was defined as the percentage change in the credit quality of the four-digit standard industrial classification (SIC) to which the loan belongs.

The correlation between portfolio return and credit quality provides a useful measure for portfolio pricing because the variation of an existing loan portfolio can be reduced by adding loans in industries with business cycles that run counter to the business cycle of the bank's portfolio. The underlying concept is that a firm's credit quality is most likely to deteriorate during business downturns. If a firm's business cycle trough occurs counter to that of the loan portfolio's business cycle trough, then adding a counter-cyclical firm's loan to the portfolio can potentially reduce portfolio return variation. [Chmura 1995] Since managers of credit institutions are generally risk averse, they are expected to place greater value on industries that reduce the total variability of the portfolio's return.

2.4.4. Macroeconomics

Ward and Neubig (1997) state that the analysis of macroeconomic indicators can offer credit institutions warning signs when used in addition to such tools as credit scoring systems. For example, the fluctuations in consumer delinquency rates across time are related to certain macroeconomic factors. The key is to identify the macroeconomic factors useful in predicting future changes in consumer delinquencies,

rather than those that occur simultaneously or after a change in delinquencies. It is leading macroeconomic indicators that are key.

One such indicator is business failures. The average annual percentage changes in both liabilities of failed businesses and credit card delinquencies have moved together in the last six years. These two variables are seen not only to move together but in fact a change in business failures typically precedes a change in the delinquency rate. Additionally, more than just a positive correlation exists between business failures and credit card delinquencies; a causal relationship exists. When analyzed using monthly data, the change in liabilities of failed businesses acts as a leading economic indicator or predictor of delinquency trends. [Ward & Neubig 1997]

The following are some of the tactical choices of an institution when utilizing economic indicators: Change portfolio allocations; increase scoring system thresholds for portfolios subject to higher risk of credit loss; lower scoring system thresholds for portfolios subject to lower risk of credit loss; and increase/decrease size of collection staffs in anticipation of increased/decreased delinquencies. [Ward & Neubig 1997]

Strategic decisions could include: Shifting portfolio allocations between various types of consumer debt; focusing credits in a particular region of the country or a unique demographic portfolio segment; reducing exposure to long-term credit risk by securitizing or selling certain portfolio segments. [Ward & Neubig 1997]

2.4.5. Risk in Loan Portfolios

Lyons (1994) states that managers of credit institutions attempt to limit default risk through loan portfolio diversification by borrower, type of loan, industry, or

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geography. The goal is to reduce the importance of any single borrower, thereby reducing the potential effect on the portfolio of a loan loss from a single borrower. Diversification also reduces the likelihood of several loans going bad at one time, increases the predictability of loan losses, and reduces potential fluctuations in future bank earnings.

Concentration risk as defined by Kao and Kallberg (1994) is the risk that individual loans in a portfolio may experience unexpected losses simultaneously due to the effect of certain common factors. No specific formula for determining the extent of loan concentrations has yet been proposed by the Federal Reserve, but it is likely that a credit institution's ability to manage such risks will be factored into existing rules for determining capital adequacy. Kao and Kallberg address four issues related to loan concentration – asset and liability management, loan loss estimation, calculation of risk correlations, and the impact of portfolio risk concentration on the loan pricing. They identify three approaches to correlation calculation: Use of credit industry default rate data, use of the bank's own default data, and use of industry credit rating or bond data. In this third approach, default or bond rating drifts can be used to measure the co-movement of industry groups. Using this approach, risk is defined as the standard deviation of credit ratings over time. However, credit ratings are applicable to a limited future time period and do not consider the present value of potential credit losses. Therefore, risk concentration is the correlation of credit rating changes and not unexpected losses over time.

2.4.6. Other Modern Portfolio Theory Frameworks

In addition to the work of Markowitz, other MPT frameworks include a linear programming single index model or SIM [Sharpe 1967], the Capital Asset Pricing Model or CAPM [Fama 1976], Arbitrage Pricing Theory or APT [Ross 1976], and the State Preference Model [Copeland & Weston 1988].

2.5. Business Failure Prediction

2.5.1. Causes of Business Failure

The overwhelming cause of individual firm failures is managerial incompetence. In 1980, over 94% of all failures were identified with the lack of experience or unbalanced experience (50%), or just plain incompetence (44%). The remaining causes are categorized as neglect (0.8%), fraud (0.5%), and reasons unknown (3.5%). [Altman 1983] These statistics represent the opinions of informed creditors and information from Dun and Bradstreet reports for over 17,000 business failures. Of course, if debtors' management were asked why businesses fail, the category of inexperience and incompetence would receive much lower significance. Argenti (1976) states that the collapse of firms occurs not suddenly, but with clear signposts of impending disaster.

There are also conditions at the aggregate level that can be expected to impact a firm's propensity to fail. The following categories of aggregate economic behavior are specified as potentially revealing indicators of business failure [Altman 1983]:

1. Economic growth activity

2. Credit availability or money market activity

3. Capital market activity

4. Business population characteristics

5. Price level changes

It should be made clear that in almost all cases the fundamental business failure problems lie with the firm itself.

2.5.2. Credit Union Failure Prediction

Collins (1980) conducted a study to determine the causes of credit union failure. The data for the study were provided by the NCUA in the form of annual reports of all federally chartered credit unions from 1956 to 1976. Data on the liquidation results of individual institutions were also obtained from the NCUA files. Included in the sample were all the federally chartered credit unions that failed with a negative net worth from 1960 through 1971 and that had been in operation more than four years. These two constraints greatly reduced the number in the sample from the 3,230 total liquidations during this period, because a substantial number of credit unions either liquidate for reasons other than insolvency and pay a liquidating dividend, or never really get started and liquidate before their fifth year of operation. A study of the distribution of losses of liquidating credit unions by length of time chartered showed that 74.3% of the losses from unsuccessful liquidations come from institutions that liquidate after the fourth year. Therefore, these restrictions greatly reduce the sample size but still catch most of the lost shares. After this group was identified and institutions with incomplete records were eliminated, 162 credit unions were left in the sample. These were matched with a

randomly-selected sample of 162 records from institutions that were chartered prior to 1956 and were still in existence at the end of the sample period making a total sample of 324.

Using step-wise multiple regression and an initial set of 28 variables, Collins found the following variables provided the best forecast of credit union failure:

- **Dividend rate.** This is the best single predictor of failure. This is a direct signal from management about their evaluation of the health of the institution.

- **Liquidity ratio.** Cash + securities divided by total assets as a measure of liquidity.

- **Delinquent loan ratio.** Delinquent Loans divided by total loans as a measure of the likelihood of future asset losses.

- **Total assets.**

- **Reserves.** Reserves divided by risk assets as a measure of the ability to withstand asset losses.

- **Activity ratio.** New loans divided by total loans as a measure of activity.

- **Variation of membership.** One would expect that large changes in membership would add stress to the management of a credit union.

These variables can be tied directly to the solvency of the companies comprising credit unions' fields of membership. Collins' results permit financial regulatory agencies to construct simple but effective early warning systems to monitor credit unions.

2.5.3. New Business Formation and Age of Business Failures

The rate of business formation can affect the failure rate in subsequent periods, since it is well documented that there is a greater propensity for younger firms to fail than for more mature companies. Table 2 shows this propensity and breaks down failures by age for different sectors and for all concerns. Note that more than 53% of all firms that failed did so in the first five years of their life. This percentage has been remarkably stable over the years, with the rate between 53 and 60% since 1952. Before 1952 an even higher percentage of younger firms failed.

Table 2: Age of Failed Businesses by Function --1980

Age in Years	Manufacturing	Wholesale	Retail	Construction	Service	All Concerns
One Year or Less	0.7%	0.9%	1.1%	0.5%	1.3%	0.9%
Two	8.3	8.5	11.7	54.3	11.2	9.6
Three	14.6	13.4	18.2	11.1	14.6	15.3
Total Three Years or Less	23.6	22.8	31.0	16.9	27.1	25.8
Four	12.3	16.1	16.6	15.7	14.2	15.4
Five	11.4	11.5	13.3	12.8	10.6	12.4
Total Five Years or Less	47.3	50.4	60.9	45.4	51.9	53.6
Six	9.3	8.6	8.7	9.5	8.6	8.9
Seven	6.7	5.9	5.5	7.9	6.8	6.3
Eight	4.8	5.5	4.7	6.2	5.8	5.2
Nine	5.0	4.4	3.1	5.4	5.4	4.3
Ten	3.0	4.3	2.9	4.1	3.1	3.4
Total Six – Ten Years	28.8	28.7	24.9	33.1	29.7	28.1
Over Ten Years	23.9	20.9	14.2	21.5	18.4	18.3
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Number of Failures	1,599	1,284	4,910	2.355	1,594	11,742

Source: Dun & Bradstreet, Failure Record, 1980, p. 10.

Although almost 28% of the firms that failed did so in their first three years, only about 1% failed in the first year. This is not surprising since it takes time to fail. Even when a firm is in its worst competitive situation (i.e. when it first starts out), there is usually sufficient capital to keep it going for a period of time, and default on loans is usually not immediate.

2.5.4. Ratio Analysis, MDA and Altman's Z-Score

The detection of company operating and financial difficulties is a subject that has been particularly amenable to analysis with financial ratios. Prior to the development of quantitative measures of company performance, agencies were established to supply a qualitative type of information assessing the credit-worthiness of particular merchants. Formal aggregate studies concerned with the prediction of business failure were evident in the 1930s and continued through the 1970s. These studies implied a definite potential of ratios as predictors of bankruptcy. In general, ratios measuring profitability, liquidity, and solvency prevailed as the most significant indicators. The order of their importance is not clear since almost every study cited a different ratio as being the most effective indication of impending problems.

The Z-Score was developed by Edward I. Altman (1968) from an analysis of 33 failed and 33 successful companies. Altman's system, basically a bankruptcy or insolvency predictor, can be used to determine if a company is a good investment. [Inc. Online 1998] There have been many other bankruptcy predictors developed and

published. However, none has been so thoroughly tested and broadly accepted as Altman's Z-Score. [Aikins 1997]

Altman's model was developed using step-wise multiple discriminate analysis (MDA). Although not as popular as regression analysis, MDA has been utilized in a variety of disciplines since its first application in the 1930s. During those earlier years, MDA was used mainly in the biological and behavioral sciences. In recent years, this technique has become increasingly popular in the practical business world as well as in academia.

MDA is a statistical technique used to classify an observation into one of several *a priori* groupings dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form (i.e. bankrupt or not bankrupt). Therefore, the first step is to establish explicit group classifications. The number of original groups can be two or more.

After the groups are established, data are collected for the objects in the groups: MDA in its most simple form attempts to derive a linear combination of these characteristics which "best" discriminates between the groups. If a particular object has characteristics that can be quantified for all of the companies in the analysis, the MDA determines a set of discriminant coefficients. When these coefficients are applied to the actual ratios, a basis for classification into one of the mutually exclusive groupings exists. The MDA technique has the advantage of considering an entire profile of characteristics common to the relevant firms, as well as the interaction of these properties. A univariate

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study, on the other hand, can only consider the measurements used for group assignments one at a time.

When utilizing a comprehensive list of financial ratios in assessing a firm's bankruptcy potential, there is reason to believe that some of the measurements will have a high degree of correlation or collinearity with each other. While this aspect is not serious in discriminant analysis, it usually motivates careful selection of the predictive variables (ratios). It also has the advantage of potentially yielding a model with a relatively small number of selected measurements that convey a great deal of information. This information might very well indicate differences among groups, but whether or not these differences are significant and meaningful is a more important aspect of the analysis.

Perhaps the primary advantage of MDA in dealing with classification problems is the potential of analyzing the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics. Combinations of ratios can be analyzed together in order to remove possible ambiguities and misclassifications observed in earlier traditional ratio studies.

Altman's first result was a formula with 22 functions (financial ratios). The function that contributed the least to discriminating between the failed and successful companies was dropped and the model was run again. This process was repeated through multiple iterations, each time dropping the ratio which least contributed to discriminating between the failed and successful companies. Five functions remained and these five measures are objectively weighted and summed up to arrive at an overall score that then becomes the basis for classification of firms into one of the *a priori* groupings.

As mentioned above, Altman's initial sample was composed of 66 corporations with 33 firms in each of the two groups. The bankrupt group (Group 1) consisted of firms that had filed for bankruptcy under Chapter X of the National Bankruptcy Act from 1946 through 1965. The mean asset size of these firms was $6.4 million, with a range of between $0.7 million and $25.9 million. Recognizing that this group was not completely homogeneous (due to industry and size differences), Altman attempted to make a careful selection of nonbankrupt firms. Group 2 consisted of a paired sample of firms chosen on a stratified random basis. The firms were stratified by industry and by size, with the asset size range restricted to between $1 and $25 million. The mean asset size of the firms in Group 2 ($9.6 million) was slightly greater than that of Group 1, but matching exact asset size of the two groups was deemed unnecessary. Firms in Group 2 were still in existence in 1966. Also, the data collected were from the same years as those compiled for the bankrupt firms. For the initial sample test, the data were derived from financial statements dated one annual reporting period prior to bankruptcy. The data were derived from *Moody's Industrial Manuals* and selected annual reports. The average lead time of the financial statements was approximately seven and one-half months.

Atman faced the important issue of determining the asset-size group to be sampled. The decision to eliminate both the small firms (under $1 million in total assets) and the very large companies from the initial sample essentially is due to the asset range of the firms in Group 1. In addition, the incidence of bankruptcy in the large-asset-size firms was quite rare prior to 1966. The absence of comprehensive data negated the representation of small firms. An argument is that financial ratios, by their very nature, have the effect of deflating statistics by size, and that therefore a good deal of the size

effect is eliminated. The Z-Score model appears sufficiently robust to accommodate large firms.

After Altman defined the initial groups and selected firms, balance sheet and income statement data were collected. Because of the large number of variables found to be significant indicators of corporate problems in past studies, a list of 22 potentially helpful variables (ratios) were identified for evaluation. The variables were classified into five standard ratio categories, including liquidity, profitability, leverage, solvency, and activity. The ratios were chosen on the basis of their popularity in the literature and their potential relevancy to the study.

From the original list of 22 variables, five were selected as doing the best overall job together in the prediction of corporate bankruptcy. This function was found to do the best job among the alternatives which included numerous computer runs analyzing different ratio profiles.

In order to arrive at the final profile of variables, the following procedures were utilized:

1. Observation of the statistical significance of various alternative functions including determination of the relative contributions of each independent variable.

2. Evaluation of intercorrelations among the relevant variables.

3. Observation of the predictive accuracy of the various profiles.

4. Judgment of the analyst.

Altman's final discriminant function (Z-Score) is calculated using the following formula [Altman 1983]:

$Z = 1.2A + 1.4B + 3.3C + 0.6D + 0.999E$

Where the variables A through E, which are all financial ratios, are defined as follows

[Eidleman 1995]:

A = Working capital to total assets (also known as liquidity). Generally when a company experiences financial difficulties, working capital will fall more quickly than total assets, causing this ratio to fall. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets. Of the three liquidity ratios evaluated by Altman, this one proved to be the most valuable.

B = Retained earnings to total assets (also known as cumulative profitability). Retained earnings is the account which reports the total amount of reinvested earnings and/or losses of a firm over its entire life. The account is also referred to as earned surplus. To some degree, the ratio reflects the age of a company because the younger it is, the less time it has had to build up cumulative profits. This bias in favor of older firms is not surprising, given the high failure rate of young companies. When a company begins to lose money, the value of total retained earnings begins to fall. For many companies, this value will become negative.

C = Earnings before interest and taxes (EBIT) to total assets. This measure of a company's operating efficiency separated from any leverage effects is calculated by dividing a company's EBIT by its total assets. It recognizes operating earnings as a key to long-run viability. It is also a measure of how productively a company is using its borrowed funds. If the ratio exceeds the average interest rate a company pays on loans, the company is making more money on the loans than it is paying in interest. Insolvency in a bankrupt sense occurs when the total liabilities exceed a fair valuation of the firm's assets with value determined by the earning power of the assets.

D = Market value of equity to book value of debt (also known as the gearing ratio). This ratio is the inverse of the more familiar debt to equity ratio and is found by dividing a company's net worth or market value by its total liabilities. It adds a market dimension to the Z-Score and academic studies of stock markets suggest that security price changes may foreshadow upcoming problems. Equity is measured by the combined market value of all shares of stock, preferred and common, while liabilities include both current and long term. The measure shows how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent.

E = Sales to Total Assets. This is a standard capital turnover measure illustrating the sales generating ability of the firm's assets. It is one measure of management's capacity in dealing with competitive conditions. This ratio is quite important because it is the least significant ratio on an individual basis. Because of its unique relationship to other

variables in the model, the sales/total assets ratio ranks second in its contribution to the overall discriminating ability of the model. This ratio can vary greatly from one industry to another.

The information for these ratios can be found in a company's financial statements. The ratios are then multiplied by the coefficients or weight factors and summed to yield the Z-Score for a company. All the ratios are constructed so that a higher value for a specific ratio is better than a lower value. Therefore, the higher the value of the Z-Score, the better off the company is and the lower the probability of bankruptcy.

Financially sound companies show Z-Scores above 2.99, while those scoring below 1.81 are found to be in fiscal danger and maybe even heading toward bankruptcy. [Eidleman 1995] Scores that fall between these ends ("zone of ignorance") indicate potential trouble but are susceptible to classification error. Upon further analysis, Altman found the range of values that resulted in the minimum number of misclassifications was 2.67 to 2.68. Therefore 2.675, the midpoint of the interval, is chosen as the Z-Score that discriminates best between the bankrupt and non-bankrupt companies. In Altman's initial study of 66 companies, Z-Scores achieved an accuracy rate of 95% in predicting the success or failure of the companies. [Aikens 1997]

Although the numbers used to calculate the Z-Score are often influenced by external factors, it provides a good analysis of where a company stands compared to the competition, and a good tool for analyzing the ups and downs of a company's financial stability over time. This model has proven to be a reliable tool for bankruptcy forecasting in a wide variety of contexts and markets. In a recent study, it correctly predicted 72% of bankruptcies two years prior to the event. Z-Score profiles for failing businesses often indicate a consistent downward trend as they approach bankruptcy. [Eidleman 1995]

Practitioners have found two very useful application areas for the Z-Score: credit risk analysis for lending decisions and bond analysis. Other areas include portfolio management, dividend and price change analysis, audit risk, and legal analyses.

2.5.5. *Other Insolvency Models*

Other insolvency prediction models include:

Springate Model (1978) – used step-wise multiple discriminate analysis (MDA) to select four financial ratios that best distinguished between sound businesses and those that actually failed. It achieved an accuracy rate of 92.5% using the 40 companies tested by Springate. Other tests of the model by Botheras (1979) and Sands (1980) yielded accuracy rates between 83.3% and 88.0%.

Fulmer Model (1984) – used step-wise multiple discriminate analysis and selected nine financial ratios. Fulmer reported a 98% accuracy rate in classifying the 40 test companies one year prior to failure and an 81% accuracy rate more than one year prior to bankruptcy.

Blasztk System (1984) – does not use MDA. Financial ratios for the company to be evaluated are calculated, weighted and then compared with ratios for average companies in that same industry as given by Dunn & Bradstreet. One of this method's strengths is that it does compare the company being evaluated with companies in the same industry.

CA-Score (1987) – used step-wise MDA. Financial ratios from the previous one and two periods are used. This model as reported by Bilanas (1987), has an average reliability rate of 83% and is restricted to evaluating manufacturing companies.

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3. Methodology

3.1. Mean-Variance Optimization (MVO)

The mean-variance portfolio optimization methodology to be employed requires a return measure and a risk measure for each of the assets (industries in the **general** case and select employee groups or SEGs in the **individual credit union** case). The first step will be to model a general case using data from all industries. From this data, the goal is to create optimal portfolios which show the allocations to each industry. This will serve as an exploration of portfolio theory applied to multiple group credit unions. Next, the approach will be to examine actual credit unions' fields of membership and apply the optimization methodology to determine industries or companies to which the credit unions could market its services in an effort to reduce their risk.

3.1.1. Return

In the general case, return (which we will define as "health" or "solvency") at the asset level will be calculated from an industry's mean Z-Score over 40 fiscal quarters (1987-1997). These health values are derived from the Z-Scores of a database of individual companies and aggregated along primary (2-digit) SIC code. In the individual credit union case, the mean Z-Scores of the companies in the SEG portfolio (field of membership) are used as health values.

Data for the general case Z-Score calculations will be collected from the Compustat® database of companies using the financial analysis software package PC Plus. The Compustat® database contains current and historical data on over 8,700 U.S.

& Canadian Corporations. (Standard & Poor's Compustat (SPC) is a division of McGraw Hill, Inc. The program S&P PCPlus for Windows® is a financial analysis tool that uses SPC's Compustat® financial database.)

The weight applied to each return is the fraction of the portfolio invested in that asset. If R_P is the return on the portfolio and X_i is the fraction of the investor's funds invested in the ith asset, then

$$R_P = \sum_{i=1}^{N} X_i R_i$$

The expected return is also a weighted average of the expected returns on the individual assets. Taking the expected value of the expression just given for the return on a portfolio yields

$$\overline{R}_P = E(R_P) = E\left(\sum_{i=1}^{N} X_i R_i\right)$$

The expected value of the sum of various returns is the sum of the expected values. Therefore, we have

$$\overline{R}_P = \sum_{i=1}^{N} E(X_i R_i)$$

The expected value of a constant times a return is a constant times the expected return, or

$$\overline{R}_P = \sum_{i=1}^{N} X_i \overline{R}_i$$

In our general case, the expected value of the portfolio health is the weighted sum of the industry SIC expected Z-Scores (health values). For the individual credit union case, we state that the expected value of the credit union's health (SEG portfolio Z-Score or FOM Z-Score) is the weighted sum of the expected value of the individual SEG Z-Scores.

3.1.2. Risk

While risk of a stock portfolio is defined as the variation of returns, the concept of risk for a credit union is tied to the overall risks associated with the field of membership or SEG portfolio. Data concerning the credit quality of industry or portfolio segments yields more information about the inherent risk of the portfolio than does data concerning the variation of returns to the industry.

In the general case, risk is defined as the variation of industry credit quality or the variance of the change in quarterly industry Z-Scores over the period 1987 to 1997. The variance shows the average deviation from the industry's mean quarterly credit quality change over time. To illustrate this, Figures 4 and 5 plot the credit quality change (percent change of quarterly Z-Score) of companies in the Primary Metal Industries (SIC 33) and Motion Pictures companies (SIC 78) for 40 fiscal quarters between 1987 and 1997.
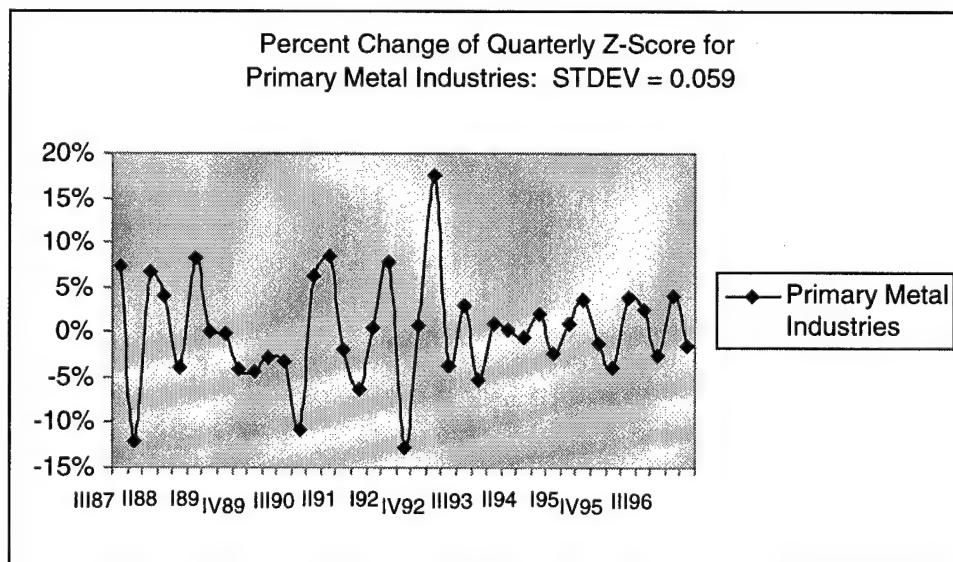
Figure 4. Percent Change of Quarterly Z-Score for Primary Metal Industries
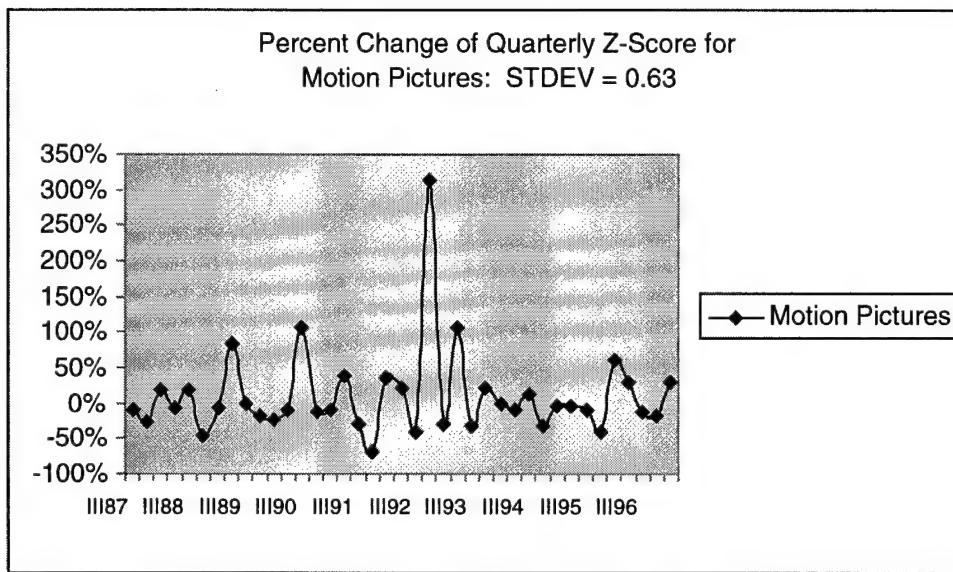
Figure 5: Percent Change of Quarterly Z-Score for Motion Pictures

The standard deviation of the Primary Metal Industries over this period is found to be 0.059 (a narrow band of change between approximately ± 15%) and for Motion Pictures to be 0.63 (a wide band of change varying between –70% and +300%).

In the individual credit union case, asset risk is the variation of a SEG's change in Z-Score over a time interval.

For our portfolio analysis, the variance of each asset's (industry's) Z-Score is multiplied by the square of the proportion invested in that industry. The first part of the expression for portfolio variance is the sum of the variances on the individual assets multiplied by the square of the proportion invested in each, or

$$\sum_{i=1}^{N} X_i^2 \sigma_i^2$$

The second set of terms in the portfolio variance is covariance terms. Covariance measures the strength of the inter-relationships of industry credit quality. For instance, if

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the credit quality of the steel industry and the auto industry move together, then the portfolio is exposed to similar risks despite the fact that the portfolio appears diversified between steel and autoworkers.

Industry credit quality moves with changes in the economy and changes in financial leverage. For example, during an economic recession, credit quality of the heavy manufacturers (Primary Metals, Fabricated Metals, Industrial Machinery and Equipment) tends to deteriorate at the same time and about the same rate, indicating a strong inter-industry relationship or high positive covariance. [Gollinger & Morgan 1993] For this thesis, industry covariances are derived using the change in average quarterly industry Z-Scores for the period 1987 to 1997.

We find that the covariance between each pair of assets in the portfolio enters the expression for the variance of a portfolio and that each covariance term is multiplied by two times the product of the proportions invested in each asset. The following captures the covariance terms:

$$\sum_{j=1}^{N} \sum_{\substack{k=1 \\ k \neq j}}^{N} X_j X_k \sigma_{jk}$$

Putting together the variance and covariance parts of the general expression for portfolio variance yields

$$\sigma_P^2 = \sum_{j=1}^{N} X_j^2 \sigma_j^2 + \sum_{j=1}^{N} \sum_{\substack{k=1 \\ k \neq j}}^{N} X_j X_k \sigma_{jk}$$

This expression represents the degree of riskiness in the portfolio; the degree to which credit quality varies over time. The contribution to the portfolio variance of the variance

of individual assets goes to zero as N gets very large. However, the contribution of the covariance terms approaches the average covariance as N gets large. The individual risk of assets can be diversified away but the contribution to the total risk caused by the covariance terms cannot.

3.1.3. The Efficient Frontier

Health and credit quality are assumed to be monotonically related, so that variations in credit quality directly translate into variations in health. The *efficient frontier* is determined by minimizing the risk associated with any given level of return.

There are two fundamental constraints on the optimization problem:

1. The sum of the proportions of each industry/SEG represented in the portfolio must equal one.

2. All industries/SEGs must have positive or zero representation in the portfolio (non-negativity).

The efficient frontier is created by varying returns between the minimum-risk portfolio and the maximum-health portfolio.

Formulated as a mathematical program, the problem is

Minimize

$$\sum_{j=1}^{N} X_j^2 \sigma_j^2 + \sum_{j=1}^{N} \sum_{\substack{k=1 \\ k \neq j}}^{N} X_j X_k \sigma_{jk}$$

Subject to

$$\sum_{i=1}^{N} X_i = 1$$

$$R_P = \sum_{i=1}^{N} X_i R_i$$

$X_i \geq 0, \ i = 1, \ldots, N$

By charter, many credit unions are designed to cater to only specific industry groups. In risk terms, this can create an unhealthy concentration. If given the opportunity to diversify, the portfolio optimization process can provide credit unions with insight into the industries to which they should focus marketing efforts. In the banking community, an industry is considered to be a concentration if loan commitments to the industry exceed 25% of the bank's capital. [Examining Circular 219, OCC 1986]

4. Application

4.1. General Model

As demonstrated, for the application of the Markowitz portfolio optimization model to credit unions, industry groups or SEGs are treated as individual securities. For various levels of health, the model solves for the optimal weights for each industry group in the member group portfolio which yield the minimum level of risk. This process generates the efficient frontier.

The Microsoft Excel Solver was employed to run the nonlinear optimization. The Excel Solver uses the Generalized Reduced Gradient (GRG2) Algorithm for optimizing nonlinear problems. This algorithm was developed by Leon Lasdon, of the University of Texas at Austin, and Allan Waren, of Cleveland State University. [Lasdon & Waren, 1978]

For the general model, efficient frontiers were calculated for an unconstrained case (no constraint on the maximum percentage of a particular industry group) and for a constrained case (no one industry group may account for more than 10% of the portfolio). Figure 6 shows the two efficient frontiers. Altman's failure thresholds of 1.81 and 2.675 are represented by dotted lines in the figure. Note that the unconstrained curve contains both the maximum health and minimum risk portfolios and that all portfolios in both cases fall above the likely failure line.

Tables 3 and 4 show the industry compositions for various levels of health for the constrained and unconstrained cases, respectively.
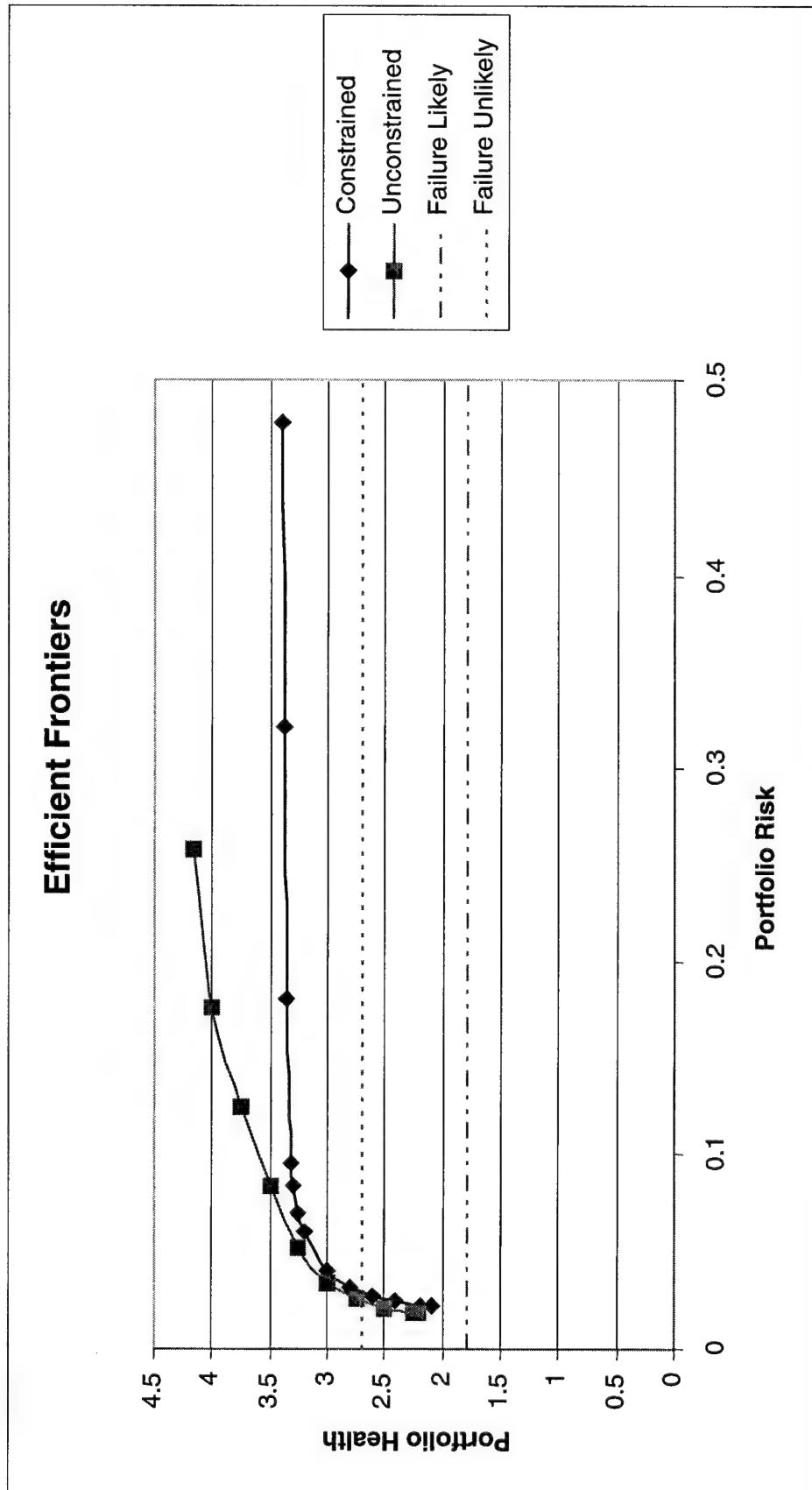
Figure 6: Efficient Frontiers – Portfolio Health

Table 2: Optimal Industry Portfolios Constrained to 10% Per Industry

SIC CODE	PORTFOLIO RISK (STDEV) --> PORTFOLIO HEALTH (Z-SCORE) -->	MIN RISK 0.0220 2.0830	0.0223 2.2000	0.0243 2.4000	0.0277 2.6000	0.0325 2.8000	0.0408 3.0000	0.0598 3.2000
1	AGRICULTURAL PRODUCTION - CROPS							0.73%
2	AGRICULTURAL PRODUCTION - LIVESTOCK			1.01%	1.83%	3.01%	6.27%	10.00%
10	METAL MINING	2.92%	3.41%	3.17%	3.01%	3.38%	5.01%	0.60%
12	COAL MINING	10.00%	10.00%	9.99%	5.14%			
14	NONMETALLIC MINERALS, EXCEPT FUELS	0.61%	0.20%					
15	GENERAL BUILDING CONTRACTORS	5.10%	4.80%	3.41%	2.52%	0.73%		
16	HEAVY CONSTRUCTION CONTRACTORS	0.86%	0.69%	0.49%	0.45%			
20	FOOD AND KINDRED PRODUCTS	3.03%	8.17%	10.00%	10.00%	10.00%	10.00%	10.00%
23	APPAREL AND OTHER TEXTILE PRODUCTS					0.94%	1.30%	1.65%
24	LUMBER AND WOOD PRODUCTS							
25	FURNITURE AND FIXTURES	4.07%	3.45%	2.64%	3.26%	4.89%	4.52%	
26	PAPER AND ALLIED PRODUCTS	0.28%	1.77%					
27	PRINTING AND PUBLISHING				1.79%	3.74%	3.24%	7.16%
28	CHEMICALS AND ALLIED PRODUCTS			2.87%	7.65%	10.00%	10.00%	10.00%
29	PETROLEUM AND COAL PRODUCTS	5.60%	3.37%					
30	RUBBER AND MISCELLANEOUS PLASTICS PRODUCTS	10.00%	10.00%	10.00%	10.00%	10.00%	7.57%	
31	LEATHER AND LEATHER PRODUCTS	9.41%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
33	PRIMARY METAL INDUSTRIES	9.31%	4.55%	4.16%	2.52%			
35	INDUSTRIAL MACHINERY AND EQUIPMENT		0.74%	2.14%	3.20%	4.60%	2.84%	
36	ELECTRICAL AND ELECTRONIC EQUIPMENT							4.92%
38	INSTRUMENTS AND RELATED PRODUCTS		2.35%	8.10%	10.00%	10.00%	10.00%	10.00%
42	MOTOR FREIGHT TRANSPORTATION AND WAREHOUSING	7.29%	6.29%	3.17%	3.14%	0.98%		
46	PIPELINES, EXCEPT NATURAL GAS	9.05%	6.80%	2.97%				
50	WHOLESALE TRADE - DURABLE GOODS	4.79%	6.27%	7.17%	5.81%	3.70%		
52	BUILDING MATERIALS, HARDWARE, GARDEN SUPPLY	1.47%	1.37%	2.26%	2.53%	1.85%		
53	GENERAL MERCHANDISE STORES	0.02%		0.28%	2.68%	3.77%		
54	FOOD STORES	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	
55	AUTOMOTIVE DEALERS AND GASOLINE SERVICE	4.44%	3.95%	4.08%	2.02%	1.37%		
56	APPAREL AND ACCESSORY STORES					3.05%	10.00%	10.00%
59	MISCELLANEOUS RETAIL						1.22%	7.74%
70	HOTELS, ROOMING HOUSES, CAMPS, AND OTHER LODGING	0.82%	0.90%	0.93%	0.86%	0.88%	0.79%	
72	PERSONAL SERVICES							6.54%
73	BUSINESS SERVICES							
76	MISCELLANEOUS REPAIR SERVICES	0.62%	0.58%	0.62%	0.62%	0.67%	0.68%	0.64%
78	MOTION PICTURES	0.29%	0.34%	0.57%	0.53%	0.46%		
80	HEALTH SERVICES							
82	EDUCATIONAL SERVICES				0.44%	1.95%	6.54%	10.00%
83	SOCIAL SERVICES							

SIC CODE	PORTFOLIO RISK (STDEV) --> PORTFOLIO HEALTH (Z-SCORE) -->	0.0698 3.2500	0.0844 3.3000	0.0959 3.3250	0.1811 3.3500	0.3213 3.3750	MAX Z 0.4784 3.4014
1	AGRICULTURAL PRODUCTION - CROPS	3.86%	8.51%	10.00%	10.00%	10.00%	10.00%
2	AGRICULTURAL PRODUCTION - LIVESTOCK	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
10	METAL MINING						
12	COAL MINING						
14	NONMETALLIC MINERALS, EXCEPT FUELS						
15	GENERAL BUILDING CONTRACTORS						
16	HEAVY CONSTRUCTION CONTRACTORS						
20	FOOD AND KINDRED PRODUCTS	10.00%	10.00%	0.00%	0.00%	0.00%	0.00%
23	APPAREL AND OTHER TEXTILE PRODUCTS	0.03%					
24	LUMBER AND WOOD PRODUCTS						
25	FURNITURE AND FIXTURES						
26	PAPER AND ALLIED PRODUCTS						
27	PRINTING AND PUBLISHING	2.60%					
28	CHEMICALS AND ALLIED PRODUCTS	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
29	PETROLEUM AND COAL PRODUCTS						
30	RUBBER AND MISCELLANEOUS PLASTICS PRODUCTS						
31	LEATHER AND LEATHER PRODUCTS	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
33	PRIMARY METAL INDUSTRIES						
35	INDUSTRIAL MACHINERY AND EQUIPMENT						
36	ELECTRICAL AND ELECTRONIC EQUIPMENT	3.07%		9.21%			
38	INSTRUMENTS AND RELATED PRODUCTS	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
42	MOTOR FREIGHT TRANSPORTATION AND WAREHOUSING						
46	PIPELINES, EXCEPT NATURAL GAS						
50	WHOLESALE TRADE - DURABLE GOODS						
52	BUILDING MATERIALS, HARDWARE, GARDEN SUPPLY						
53	GENERAL MERCHANDISE STORES						
54	FOOD STORES						
55	AUTOMOTIVE DEALERS AND GASOLINE SERVICE						
56	APPAREL AND ACCESSORY STORES	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
59	MISCELLANEOUS RETAIL	10.00%	7.55%				
70	HOTELS, ROOMING HOUSES, CAMPS, AND OTHER LODGING						
72	PERSONAL SERVICES	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
73	BUSINESS SERVICES	0.03%	3.93%	10.00%	6.96%	3.57%	
76	MISCELLANEOUS REPAIR SERVICES	0.40%					
78	MOTION PICTURES						
80	HEALTH SERVICES			0.73%	10.00%	10.00%	10.00%
82	EDUCATIONAL SERVICES	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
83	SOCIAL SERVICES			0.06%	3.03%	6.42%	10.00%

Table 4: Optimal Industry Portfolios - Unconstrained

		MIN RISK				
	PORTFOLIO RISK (STDEV) -->	0.0193	0.0194	0.0216	0.0254	0.0340
SIC CODE	PORTFOLIO HEALTH (Z-SCORE) -->	2.2113	2.2500	2.5000	2.7500	3.0000
2	AGRICULTURAL PRODUCTION - LIVESTOCK				0.11%	2.17%
10	METAL MINING	3.94%	3.94%	4.55%	3.05%	0.59%
12	COAL MINING	10.87%	9.98%	8.53%	2.16%	
14	NONMETALLIC MINERALS, EXCEPT FUELS	0.65%	0.79%	0.06%		
15	GENERAL BUILDING CONTRACTORS	4.25%	3.98%	2.06%	0.22%	
16	HEAVY CONSTRUCTION CONTRACTORS	0.92%	1.14%	2.17%	2.29%	
20	FOOD AND KINDRED PRODUCTS	0.56%	1.44%	10.94%	14.30%	11.20%
21	TOBACCO MANUFACTURES	0.03%	0.02%	0.06%	0.12%	0.06%
28	CHEMICALS AND ALLIED PRODUCTS				2.79%	13.33%
30	RUBBER AND MISCELLANEOUS PLASTICS PRODUCTS	12.97%	13.25%	7.37%	5.32%	
31	LEATHER AND LEATHER PRODUCTS	8.87%	9.60%	14.78%	19.05%	22.39%
33	PRIMARY METAL INDUSTRIES	7.56%	7.40%	2.88%		
35	INDUSTRIAL MACHINERY AND EQUIPMENT			2.95%		
38	INSTRUMENTS AND RELATED PRODUCTS			5.76%	19.28%	30.28%
41	LOCAL AND INTERURBAN PASSENGER TRANSIT	0.04%	0.06%	0.20%	0.18%	
42	MOTOR FREIGHT TRANSPORTATION AND WAREHOUSING	5.68%	5.39%	0.06%		
46	PIPELINES, EXCEPT NATURAL GAS	5.47%	4.30%			
50	WHOLESALE TRADE - DURABLE GOODS	4.80%	4.92%	2.52%		
54	FOOD STORES	28.01%	28.56%	30.75%	29.23%	15.70%
55	AUTOMOTIVE DEALERS AND GASOLINE SERVICE	3.97%	3.89%	2.79%	0.59%	
56	APPAREL AND ACCESSORY STORES					0.19%
70	HOTELS, ROOMING HOUSES, CAMPS, AND OTHER LODGING	0.26%	0.24%	0.37%	0.28%	0.36%
72	PERSONAL SERVICES					
76	MISCELLANEOUS REPAIR SERVICES	0.53%	0.54%	0.29%	0.15%	0.18%
78	MOTION PICTURES	0.61%	0.57%	0.47%	0.57%	0.25%
80	HEALTH SERVICES			0.42%		
82	EDUCATIONAL SERVICES				0.33%	3.27%

						MAX Z
	PORTFOLIO RISK (STDEV) -->	0.0519	0.0833	0.1252	0.1762	0.2584
SIC CODE	PORTFOLIO HEALTH (Z-SCORE) -->	3.2500	3.5000	3.7500	4.0000	4.1586
2	AGRICULTURAL PRODUCTION - LIVESTOCK	7.70%	20.60%	34.23%	54.39%	100.00%
10	METAL MINING					
12	COAL MINING					
14	NONMETALLIC MINERALS, EXCEPT FUELS					
15	GENERAL BUILDING CONTRACTORS					
16	HEAVY CONSTRUCTION CONTRACTORS					
20	FOOD AND KINDRED PRODUCTS	0.03%				
21	TOBACCO MANUFACTURES					
28	CHEMICALS AND ALLIED PRODUCTS	22.62%	20.37%	12.04%		
30	RUBBER AND MISCELLANEOUS PLASTICS PRODUCTS					
31	LEATHER AND LEATHER PRODUCTS	18.53%				
33	PRIMARY METAL INDUSTRIES					
35	INDUSTRIAL MACHINERY AND EQUIPMENT					
38	INSTRUMENTS AND RELATED PRODUCTS	37.04%	29.33%	12.14%		
41	LOCAL AND INTERURBAN PASSENGER TRANSIT					
42	MOTOR FREIGHT TRANSPORTATION AND WAREHOUSING					
46	PIPELINES, EXCEPT NATURAL GAS					
50	WHOLESALE TRADE - DURABLE GOODS					
54	FOOD STORES					
55	AUTOMOTIVE DEALERS AND GASOLINE SERVICE					
56	APPAREL AND ACCESSORY STORES	4.46%	7.52%			
70	HOTELS, ROOMING HOUSES, CAMPS, AND OTHER LODGING	0.24%				
72	PERSONAL SERVICES		4.07%	10.35%	7.77%	
76	MISCELLANEOUS REPAIR SERVICES	0.36%	0.39%	0.60%		
78	MOTION PICTURES					
80	HEALTH SERVICES					
82	EDUCATIONAL SERVICES	9.01%	17.71%	30.62%	37.84%	

4.2. Application of Model to an Individual Credit Union

To this point we have explored the general case and described a process to determine the optimal combination of industries for a given level of health in order to minimize risk. However, no credit union contains these optimal mixes. Also, the actions a credit union would have to take to identically match the optimal portfolio allocations would likely be impractical or impossible (e.g. divestiture of current SEGs and attraction of companies fitting the identified optimal industries). However, a credit union that desires to reduce its risk can employ the optimization methodology to its field of membership portfolio. The following serves as an example of steps that a credit union could take in this regard:

1. Conduct a Z-Score analysis of all SEGs in the credit union's field of membership using historic balance sheet data over a suitable time period (e.g. past 10 years). This analysis will reveal the means, variances, and covariances of the SEG Z-Scores.

2. Determine the current portfolio allocations of each SEG. This could possibly be calculated as the fraction of the number of members in each SEG to the total membership or as the dollar value of each SEG's deposits less loans over the credit union's deposits less loans. We now have a point in the health vs. risk plane.

3. Credit union management could then determine to what level the credit union is willing to expand or divest its overall field of membership. This would take the form of constraints on the optimization algorithm. The algorithm could be run using generic industry (SIC) Z-Score data or focus on specific target companies in the geographic region established in the credit union's charter.

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4. Any other constraint requirements would be set and the optimization algorithm could then be solved. The results would reveal the industries or companies to which the credit union should focus its marketing efforts in order to reduce risk. Cluster analysis of the industry correlations could be used to find industries that could serve as suitable alternatives to those identified as optimal.

4.2.1. Case Study #1: Bronco Federal Credit Union

The first case study examines Bronco Federal Credit Union (BFCU) in Franklin, a rural community in southeast Virginia. BFCU was chartered by the Farm Credit Administration in 1941 to provide an opportunity to accumulate savings and create a source of credit for "employees" of the Chesapeake-Camp Corporation who worked at the facilities in Franklin. [BFCU Homepage 1998] Today, BFCU's field of membership includes:

1. Employees of Union Camp Corporation (UCC) who work in or are paid or supervised from Franklin, Virginia and their immediate families (defined as spouses, children of any age, parents, brothers and sisters).

2. Retirees and widow/widowers of deceased retirees and their immediate families.

3. Employees who are considered "temporary with benefits".

4. Organizations of such persons.

Union Camp Corporation operates two major facilities in Franklin: a pulp and paper mill and a fiber recycling plant. There are approximately 2,600 employees.

BFCU was selected as a candidate for study due to its field of membership consisting of a single employee group and the limited number of companies in the region that BFCU

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could recruit as possible new employee groups. Discussions with management at BFCU [Thompson 1998] revealed that they are currently considering the addition of new select employee groups in an effort to diversify. The goal of the study in this case is to identify companies in the Franklin area that, if added to BFCU's field of membership, could reduce the overall risk of credit union failure.

Table 5 below shows the 20 largest employers (excluding Union Camp) in the Franklin area. The table shows the companies, their primary industries, number of employees and 2-digit SIC codes.

COMPANY	INDUSTRY	# EMPLOYEES	2-DIGIT SIC
BIRDSONG PEANUTS	PEANUTS/SEED & HULL	150	01
SOUTHSIDE GIN	COTTON	20	01
VA-CAR PEANUT CO-OP	PEANUTS & SEED	50	01
H.P. BEALE & SONS	MEAT PACKING	12	20
HANCOCK PEANUT CO.	PEANUT PROCESSING	100	20
HUBBARD PEANUT CO.	COCKTAIL PEANUTS	15	20
R.M. FELTS PACKING CO.	MEAT PACKING	13	20
VALLEY PROTEINS, INC.	FEED SUPPLEMENTS	60	20
ATLANTIC WOOD INTUSTRIES	SALT TREAT POLES & PILINGS	28	24
BLACKWATER PALLET CO.	SHIPPING PALLETS	15	24
CHAPMAN LUMBER CO.	HARDWOOD LUMBER	32	24
PORTERS WOOD PRODUCTS	SHIPPING PALLETS	13	24
STAR PAPER	TUBE PAPER	11	26
BYERLY PUBLICATIONS	NEWSPAPERS	50	27
HERCULES, INC.	INDUSTRIAL CHEMICALS	135	28
LG&E	POWER PRODUCER	33	29
APOLLO PLASTICS	PLASTIC BOTTLES	25	30
HOT METAL PRODUCTS, INC.	STEEL FABRICATION	33	34
FRANKLIN EQUIP	INDUSTRIAL MACHINERY	400	35
NARRICOT INDUSTRIES	SEAT BELTS	421	37

Table 5: Largest Employers in Franklin, Virginia Area (Excludes Union Camp)

The next step of the analysis requires that we gather Z-Score data for the companies. Financial statements are not available for the individual companies so we will use historic data for the primary industries associated with each company. However, financial statement data for Union Camp will be used.

Figure 7 shows the behavior of Union Camp's Z-Score over the 10-year period from 1989 to 1998.
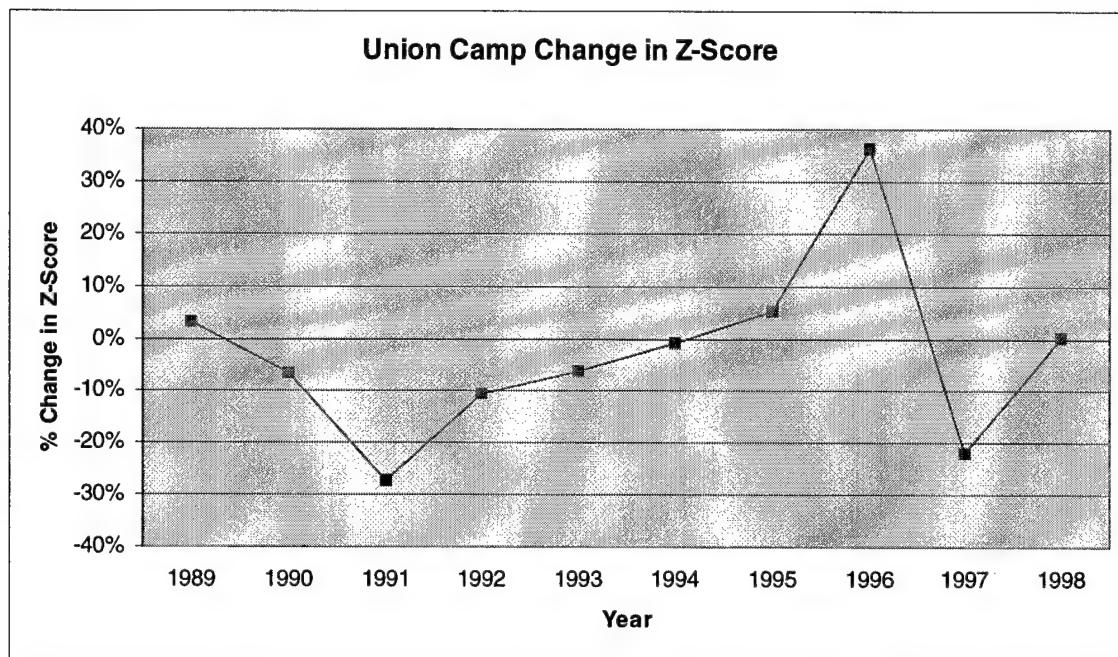

Figure 7: Union Camp Change in Z-Score 1989 - 1998

For the case study we will assume that BFCU desires a 20% increase in its current membership. This will be used as a constraint in the optimization algorithm as will the number of employees in each industry sector available in the Franklin area.

An efficient frontier (Figure 8) was created showing the optimal portfolios for each level of risk and health.
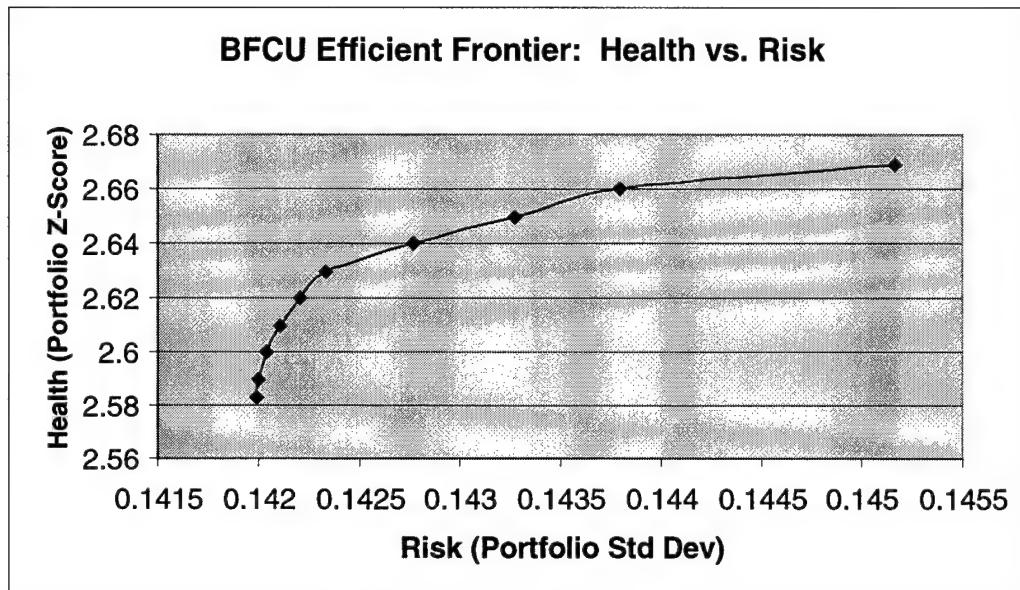
Figure 8: BFCU Efficient Frontier

BFCU management must determine its risk tolerance and health requirements in order to locate a point on the efficient frontier.

A set of optimal portfolio compositions is shown below in Table 6.

	MIN SD									MAX Z
RISK ->	0.1420	0.1420	0.1420	0.1421	0.1422	0.1423	0.1428	0.1433	0.1438	0.1452
HEALTH ->	2.5826	2.5900	2.6000	2.6100	2.6200	2.6300	2.6400	2.6500	2.6600	2.6690
UCC	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%
01	3.6%	4.3%	5.3%	6.3%	7.3%	8.3%	8.5%	8.5%	8.5%	8.5%
20										4.4%
27	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%
28							1.4%	3.0%	4.7%	5.2%
35	14.5%	13.8%	12.8%	11.8%	10.8%	9.8%	8.2%	6.6%	4.9%	

Table 6: Optimal Portfolio Compositions for BFCU

UCC's mean Z-Score as an individual company over the past 10 years is 2.495. We see that all of the new portfolios identified have health measures higher than this (in the

2.583 to 2.669 range). UCC's risk (standard deviation) is 0.173 and all of the new portfolios have risk levels below this value (in the 0.142 to 0.145 range). We also find that the minimum risk portfolio identifies the following industries for addition to BFCU's field of membership:

Table 7: BFCU Minimum Risk Portfolio Industry Groups

SIC	Industry Group
01	Agriculture Production – Crops
27	Printing and Publishing
35	Industrial Machinery and Equipment

For the maximum health portfolio, the following industries are identified:

Table 8: BFCU Maximum Health Portfolio Industry Groups

SIC	Industry Group
01	Agriculture Production – Crops
20	Food and Kindred Products
27	Printing and Publishing
28	Chemicals and Allied Products

As we would expect intuitively, the Lumber and Wood Products industry (SIC 24) is not found in the set of optimal portfolios since UCC belongs to this industry. The industries identified have risk profiles uncorrelated with UCC.

After determining the level of risk/health appropriate for the credit union, BFCU can pursue for membership the companies in the Franklin area associated with the industry groups identified by the optimization routine. By recruiting these companies, the credit union can reduce its overall risk of failure.

4.2.2. Case Study #2: Fibers Federal Credit Union

The second case study examines a credit union with different circumstances than BFCU. Fibers Federal Credit Union (FFCU) in Chester, Virginia currently is organized as a multiple group credit union and is located in the vicinity of a major metropolitan city (Richmond). FFCU serves a field of membership of approximately 5,000 members. The five primary select employee groups (shown with their stock ticker in parentheses) served by FFCU are the following:

- AlliedSignal Fiber Plants (ALD) 60%

- Coca-Cola Bottling Plant (KO) 15%

- Greyhound Bus Lines (BUS) 10%

- Lowes (LOW) 5%

- Owens & Minor, Inc. (OMI) 10%

The SEGs are also shown with the approximate percentage representation of the total field of membership for FFCU [Bollinger 1999]. The analysis in this case will assume that the credit union seeks to expand 20%. Therefore, the representations of the current SEGs will be modified as follows:

- ALD 48%

- KO 12%

- BUS 8%

- LOW 4%

- OMI 8%

The goal will be to identify industry groups to which FFCU should focus its marketing efforts as it seeks new SEGs for the credit union. To ensure that at least two

industries are identified, we constrain the individual industry representations to a maximum of 10%. The calculated efficient frontier for FFCU is shown in Figure 9:
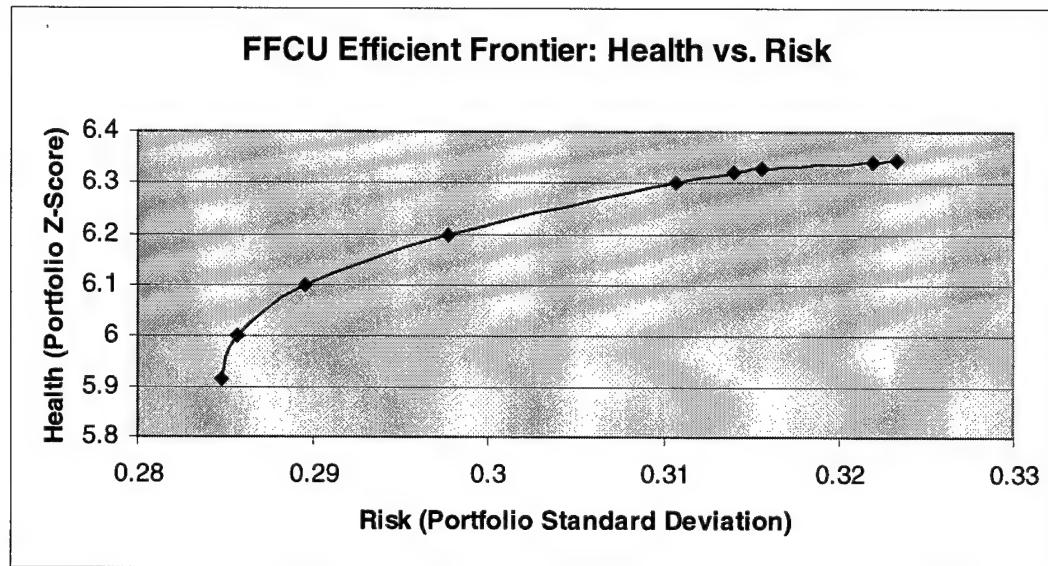

Figure 9: FFCU Efficient Frontier

A set of optimal portfolio combinations is shown below in Table 9:

	MIN SD								MAX Z
SD-->	0.285	0.286	0.289	0.298	0.311	0.314	0.316	0.322	0.323
Z-SCORE-->	5.913	6.000	6.100	6.200	6.300	6.320	6.330	6.340	6.345
1			5.2%	10.0%	9.8%	9.0%	9.6%	1.4%	
2				3.0%	8.4%	10.0%	10.0%	10.0%	10.0%
38			2.0%						
44	5.6%	3.1%							
46	4.4%								
54		6.8%	2.7%						
76	10.0%	10.0%	10.0%	6.9%	1.8%	0.9%	0.3%		
82								8.6%	9.9%
ALD	48.0%	48.0%	48.0%	48.0%	48.0%	48.0%	48.0%	48.0%	48.0%
KO	12.0%	12.0%	12.0%	12.0%	12.0%	12.0%	12.0%	12.0%	12.0%
BUS	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%
LOW	4.0%	4.0%	4.0%	4.0%	4.0%	4.0%	4.0%	4.0%	4.0%
OMI	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%

Table 9: Optimal Portfolio Combinations for FFCU

FFCU's mean Z-Score as a credit union of multiple SEGs over the past 10 years is 4.98. We see that all of the new portfolios identified have health measures higher than

this (in the 5.913 to 6.345 range). We see from this analysis that the optimal minimum risk portfolio would include the addition of water transportation (SIC 44), pipelines (SIC 46), and repair services (SIC 76). The optimal maximum health portfolio would include the addition of agricultural production – livestock (SIC 2) and educational services (SIC 82). Other optimal portfolios on the efficient frontier include the following industries: agricultural production – crops (SIC 1), instruments and related products (SIC 38), and food stores (SIC 54). FFCU management could determine their risk tolerance point on the efficient frontier, examine the identified industry groups **or** industries with high correlations with these groups, and market their services towards local area companies which fall into the identified groups.

4.3. Credit Union Marketing

In general, credit unions do not maintain large advertising budgets and few actively and aggressively market their services to potential select employee groups. Instead, companies seek out the credit unions. Those companies desiring credit union affiliation apply for inclusion in a local credit union's field of membership. If the company meets the requirements for membership, then it is accepted. The credit union will then send a representative to present a briefing to all employees of the company detailing the services offered by the credit union. [Bollinger 1999] This representative will invite and encourage the employees to join.

A recent poll of credit union managers asked the following question: Given that there is still no well-known national credit union marketing campaign in existence, have credit unions missed an opportunity to seize the momentum generated with the passage of H.R.

1151, the Credit Union Membership Access Act? In response, 81.5% of the managers stated that indeed an opportunity has been missed. [Credit Union Times 1999]

Credit unions have operated without active marketing in the past due to their non-profit nature. However, given the recent comments of NCUA Chairman D'Amours regarding the need for diversification, credit unions are likely to more carefully consider the composition of their membership portfolios. They are apt to explore techniques to attract companies to the credit union which have risk behavior uncorrelated with the risk behavior of their current fields of membership. This will help ensure the future solvency of the credit unions.

4.4. Sensitivity Analysis

One of the often identified weaknesses of modern portfolio theory is that small changes in the input data can result in large changes in the resulting portfolio compositions. The key inputs of the optimization problem are the means, variances, and covariances of the historical Z-Score data. An analysis was conducted to determine the sensitivity of the industry or SEG weightings to changes in the key inputs.

The first approach was to alter the covariance between two of the industries with heavy weightings in the BFCU case study. Both Crop Production (SIC 1) and Industrial Machinery (SIC 35) received heavy weightings in the BFCU optimal portfolios. Therefore, the covariance between these two SICs was altered to determine the effect on the portfolios. With the covariance changed from its original value of –0.00142 to a positive covariance of 0.00142, the following portfolio set was generated:

	MIN SD										MAX Z
RISK ->	0.142086	0.142089	0.142118	0.142173	0.142256	0.142366	0.142503	0.142912	0.143387	0.143874	0.145345
HEALTH ->	2.574594	2.58	2.59	2.6	2.61	2.62	2.63	2.64	2.65	2.66	2.66904
UCC	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%
1	2.8%	3.3%	4.3%	5.3%	6.3%	7.3%	8.3%	8.5%	8.5%	8.5%	8.5%
20											5.0%
27	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.3%
28								1.4%	3.0%	4.7%	5.2%
35	15.3%	14.8%	13.8%	12.8%	11.8%	10.8%	9.8%	8.2%	6.6%	4.9%	

Table 10: Change #1 – SIC 1 and 35 Covariance 0.00142

A second iteration altered the covariance between SIC 1 and 35 to an even higher

positive value of 0.008. The following portfolio set was generated:

	MIN SD											MAX Z
RISK ->	0.142271	0.142274	0.142317	0.142394	0.142488	0.1426	0.14273	0.142878	0.143234	0.143643	0.144065	0.145166
HEALTH ->	2.562422	2.57	2.58	2.59	2.6	2.61	2.62	2.63	2.64	2.65	2.66	2.669046
UCC	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%
1	1.9%	2.5%	3.3%	4.3%	5.3%	6.3%	7.3%	8.3%	8.5%	8.5%	8.5%	8.5%
20												4.4%
27	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%
28									1.4%	3.0%	4.7%	5.2%
35	15.4%	15.4%	14.8%	13.8%	12.8%	11.8%	10.8%	9.8%	8.2%	6.6%	4.9%	
37	0.8%	0.2%										

Table 11: Change #2 – SIC 1 and 35 Covariance 0.008

In both of these cases, when compared to the original portfolio compositions shown

in Table 6, only slight variations are noted in industry weightings and the health and risk

values. Additionally, no changes are noted in the individual SICs identified in the

optimal portfolios.

A third iteration reduced the mean Z-Score of Crop Production (SIC 1) from a value

of 3.6 to 2.5 (a reduction of approximately 30%). The following portfolio set was

generated:

	MIN SD					MAX Z
RISK ->	0.142271	0.142463	0.142805	0.14324	0.144027	0.145817
HEALTH ->	2.540987	2.55	2.56	2.57	2.58	2.588291
UCC	80.0%	80.0%	80.0%	80.0%	80.0%	80.0%
1	1.9%	1.8%	0.4%			
20					1.5%	7.7%
27	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%
28		0.9%	2.3%	3.9%	5.2%	5.2%
35	15.4%	15.4%	15.4%	14.2%	11.4%	5.2%
37	0.8%					

Table 12: Change #3 – SIC 1 Mean Z-Score Reduced

Again comparing the results with our original portfolio shown in Table 6, we see that a 30% reduction in the mean Z-Score of firms in the Crop Production industry would cause that industry to drop out of the optimal portfolios having health values greater than 2.56. We also note the appearance of Transportation Equipment (SIC 37) in the minimum risk portfolio. This analysis reveals the importance of accurate historic data for the industries or SICs under investigation.

4.5. Assumptions and Implications

The following are some important assumptions and implications associated with applying a mean-variance optimization model using Z-Scores to a credit union portfolio:

1. As a surrogate for portfolio return, we have defined a portfolio "health" measure calculated as the weighted sum of the mean Z-Scores for the industries or SEGs contained in the portfolio. The key factors in determining the returns for an industry/SEG are 1) current credit quality for the industry/SEG, and 2) industry/SEG-specific risk factors. Industry/SEG credit quality may be measured using a credit union's internal risk rating or by an external measure such as bond ratings or Z-Scores as was employed here. Industry/SEG-specific risk factors include economic

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fundamentals of the industry, cyclicality, technology, regulation, commodity price sensitivity, financial characteristics, and perhaps certain intangibles depending on the industry/SEG. [Gollinger & Morgan 1993] Other measures of credit union health/return may provide a better model than the Z-Score model. Credit union performance is evaluated by the National Credit Union Administration Board through the CAMEL Rating System (CAMEL stands for Capital, Assets, Management, Earnings and Liquidity). The ratings are from 1 to 5. A rating of 1 implies that the credit union is sound in every respect and resistant to external economic and financial disturbances. A rating of 5 implies that failure is imminent. The CAMEL rating is calculated using a set of financial ratios. [NCUA Letters No. 132 and 167 1992 & 1995] A credit union could attempt to determine the contribution of each SEG to the financial ratios which go into the CAMEL rating and use these "SEG CAMEL ratings" as the individual return of the assets in the portfolio optimization model. Another approach would require a credit union to calculate a rate of return generated by the members from each SEG in its portfolio. The return on assets (ROA) or return on invested capital (ROIC) of the credit union's SEGs are possible return measures worth consideration. These measures could be used to calculate the profitability and efficiency of the SEGs.

2. The risk data are based on historical variances and covariances of industry or company credit quality that may not be a good proxy for future correlations. To the extent that future industry/company correlations and health change, the efficient frontier will also change. Forecasts of industry/company credit quality and their correlations for some future period could be generated to reveal a more relevant

efficient frontier. Additionally, credit unions should employ a strategy of periodic rebalancing of the portfolio assets using updated financial data.

3. The Z-Score may not be practical to compare firms across all industries using one set of variables and coefficients. The coefficients for the variables will vary by specific industries such as heavy industrial companies versus retail firms versus service firms. This variance would be noted especially in the asset turnover ratio (variable E = sales to total assets) which varies widely for different industry groups. In some cases, the variables themselves may differ. For some industries, the ratios used in the model might change because of significant differences in their balance sheets and income statements relative to other industries.

4. An understanding of the factors affecting the correlation of industries is important. Industries may experience similar changes in credit quality for different reasons. For example, a decline in credit quality might be the result of increased leverage in one industry, while in another industry that deterioration may be the result of depressed sales. An understanding of industry linkages, end markets, and factor inputs would complement the analysis of credit quality. [Gollinger & Morgan 1993]

5. Mean-variance optimization does have its shortcomings. As mentioned in a previous section, in some cases small changes in the input data can result in large changes in the output portfolio compositions. Bernstein (1995) suggests that the following conditions be applied as criteria for the employment of MVO techniques:

   - Rebalancing must be taken into consideration. There is currently no well accepted formula which can prospectively estimate this effect, and in any case the critical line technique of MVO is difficult, if not impossible, to solve at this level

of complexity. This leaves us with spreadsheet techniques, which automatically take rebalancing into account.

- The expected returns must be reasonable. We can solve this problem by applying corrections to our periodic returns that result in a more reasonable long term return for that asset.

- There must be enough time periods available to provide a reasonably accurate estimate of the correlations between assets. Several years' worth of monthly returns or several years of quarterly returns is sufficient in this regard.

6. The model does not indicate which portfolio on the efficient frontier should be selected by the credit union. Selection of an optimal portfolio requires knowledge of a credit union's health versus risk trade-off (risk utility) preference.

5. Conclusions

5.1. General

Whether historically calculated or analyst-forecasted data (e.g. Z-Scores) are used for asset selection, portfolio optimization, or performance evaluation, considerable judgment is required and considerable controversy results. Nonetheless, the leadership at financial institutions believes that they are making better decisions by using more systematic approaches to investment management.

We must realize that there are problems with the simple-minded use of a simple concept. There are always dangers, lessened if they are known. This thesis has demonstrated that the judicious use of portfolio optimization techniques applied to the fields of membership of credit unions is a concept worth the risks.

The credit union industry is already feeling the effects of the passing of H.R. 1151. As of April 1, 1999, through the first 12 weeks of the new FOM rules implementing the law, NCUA has approved 4,125 SEGs with a total of 316,352 potential members, an average of 77 per group. [Credit Union Journal 1999] This work has shown a method that credit unions can use in their efforts to attract new SEGs.

5.2. Contributions and Areas for Future Research

From a systems engineering perspective, this work contributes a novel application of mathematical (quadratic) programming and a unique risk management framework for a

major financial services system. From a financial management perspective, a novel use of both modern portfolio theory and bankruptcy prediction has been identified.

Although this research is primarily exploratory in nature, it should serve as call to credit unions that their risk of failure can be quantitatively measured and proactively managed. It takes a step beyond the simple directive to "diversify your field of membership" and identifies a means to ensure that diversification is performed in a logical manner.

This work reveals possible future extensions and study in several areas including:

- The application of other credit union health/return measures (e.g. CAMEL, ROA, ROIC) in an effort to more effectively quantify profitability and efficiency.

- The utilization of different Z-Score models appropriate for the specific types of firms under analysis (e.g. industrial firm Z-Score versus service firm Z-Score).

In conclusion, this thesis presents valuable, original contributions and opens a new thread of research to the study of credit union management.

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